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Kumulative Dissertation

The influence of the Basel II and III frameworks on financial market stability

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Synopsis of the cumulative doctoral dissertation

Abstract

In the cumulative doctoral thesis, four papers are presented that deal with the impact of the Basel II and Basel III frameworks on financial market stability. With an empirical analysis and two heterogeneous agent models, we analyze the impact of such aspects as the choice of the VaR model within the framework, the influence of backtesting exceptions and the new proposed changes in the Basel III framework.
As a general result, we determine that too strict regulation may lead to the opposite desired effect. The Basel III framework in particular constitutes a severe intervention in the financial market, but responsible regulation may lead here to stabilization. Regulations aiming at a direct target, such as the choice of the Value-at-Risk model or the calculation of the level of regulatory capital for market risk, prove to be more effective than general rules, such as a general increase in the minimum capital requirements for all risk types of the frameworks.

Keywords: Value-at-Risk models, (stressed) Value-at-Risk, Basel II, Basel III, level of regulatory capital, bank regulation, heterogeneous agent model, Monte Carlo simulation

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This thesis deals with the analysis of the influence of the Basel II and III frameworks on financial market stability. The challenges and drawbacks of the regulations determined by these frameworks are elaborated in four papers. Since financial institutions have to connect their trading decisions with the regulatory capital which, in turn, is dependent on the risk resulting from assets they buy and sell, price movements on financial markets can be influenced by those regulations. These papers focus in identifying and measuring the possible consequences of the impact of these regulations.

We proceed as follows. First, we qualify the research context by sketching crucial aspects of the Basel II and III frameworks. We then present the methodology and (novel) research results of the four papers contained in this thesis. Finally, we draw a general conclusion by connecting the main aspects of the papers' results and highlight challenges for further research based on these results.

1 Qualifying the research context of the four publications

For the calculation of capital requirements, the Basel II framework (International Convergence of Capital Measurement and Capital Standards) differentiates between three risk types: market risk, credit risk and operational risk (BCBS 2006). For each of these risk types, regulatory capital is calculated subject to the positions the financial institutions holds in its portfolio and has in its balance sheet. In summary, these three risk types constitute the level of regulatory capital according to Basel II. The old Basel I framework was enhanced to cope with the challenges of (financial) globalization that arose over the last two decades (Crouhy et al. 2006). Adoption of the framework depends on national legislation. In most countries, including in Germany, Basel II came into force in 2007; in the US, however, the adoption process only began in 2008 and has not yet been completed (BCBS 2011c).

With the onset of the severe financial crisis in 2007 it became apparent that Basel II was not able to cope with the challenges posed by the whole host of new financial products. Financial institutions assessed as "too big to fail" collapsed or had to be rescued by bail-out (Acharya et al. 2009). It was obvious that the regulatory capital was insufficient to sustain the problems that came to light in the course of the 2007 crisis. Facing these new problems, the Basel Board on Banking Supervision (BCBS) decided to revise the Basel II framework - and launched in an enduring process regulations that constitute the Basel III framework (BCBS 2009, 2010a, 2010b, 2011a, 2011b).

In this context, we focus on the influence of these regulations on financial markets for which market risk is decisive. Market risk is defined as "the risk of change in the value of a financial position due to changes in the value of the underlying components on which that position depends," McNeil et al. (2005, p. 2). To assess the level of regulatory capital of market risk, the formulae of both Basel II and Basel III frameworks use Value-at-Risk models. In an economic sense, the Value-at-Risk of an asset portfolio held by a financial institution is the maximum loss which is not exceeded on α% of n consecutive trading days. In the Basel II framework, these are 10 trading days where $\alpha = 99\%$. It is calculated for at least the last 250 trading days (BCBS 2006, 2009). The formula is as follows:

$$cr_t = \max\left(\frac{h}{60}\sum_{i=1}^{60}\mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t)\right), \tag{1}$$

where cr_t is the capital requirements on day t, $\mathrm{VaR}_{0.99}(\mathbf{10}|t)$ the ten-step-VaR and $h/60\sum_{i=1}^{60}\mathrm{VaR}_{0.99}(\mathbf{10}|t-i)$ the 60-day average of the last 60 ten-step-VaR estimators weighted with a factor h. The BCBS does not prescribe any special model for the determination of regulatory capital. Value-at-Risk models differ strongly concerning the assumptions used for its calculation. Common Value-at-Risk models differ mainly with regard to two characteristics: which distribution shall be used for the distribution of returns and how (recent) observations should be weighted.

Concerning the first assumption, Fama (1965) and Mandelbrot (1963) found that the distribution of returns is leptokurtic, meaning the existence of more probability mass close to the mean and at the distributions´ tails (heavy-tailed distributions). Concerning the assumption of the return distribution, one may assume a specific distribution (parametric approaches), using the empirical distribution of returns (empirical approaches), or using Monte Carlo simulations or bootstrap approaches (semi-parametric approaches). Concerning the second assumption, it is important to know how recent observations are weighted. The volatility of a financial market tends to change in clusters, meaning that times with high volatility alternate with calm periods characterized by low volatility. During a change of regimes, especially during a change from a calm period to a highly fluctuating period, it is important that a Value-at-Risk model is quite quick at capturing the increase in market risk to force the financial institution to hold more regulatory capital, preparing it for higher or extraordinary losses. For this purpose, many Value-at-Risk models, such as GARCH models or the Exponential Weighted Moving Average (EWMA) approach, weight recent observation higher than observations at the beginning of the considered time period (Alexander 2001; Crouhy et al. 2001; Mc Neil et al. 2005).

In practice, financial institutions mainly use Value-at-Risk models with very simple assumptions (Homburg & Scherpereel 2005; McNeil et al. 2005). Here, the first paper of the thesis, entitled *The impact of choice of VaR models on the level of regulatory capital according to Basel II*[1], discusses possible reasons for this behavior.

Returning to the formula of calculating the level of regulatory capital (cp. Formula (1)), the decisive term of the maximum expression is the 60-day-average of the 10-step Value-at-Risk multiplied by factor h. This factor h ranges between 3 and 4. It rises above an amount of 3 if a backtesting exception occurs, which happens on average 2.5 times a year. The reason for this is that the loss associated with the Value-at-Risk measure is not exceeded on 99% trading days. Hence it is exceeded on 1% of 250 trading days per year. The BCBS assumes the model does not work well if the 1-step Value-at-Risk is exceeded more than 4 times a year. Hence, more backtesting exceptions cause a higher level of regulatory capital (Stahl 1997; BCBS 2006, 2009). This criteria is used in the second paper of the thesis, entitled *Does Basel II destablize financial markets? - An agent-based financial market perspective*[2], to test the impact of such a sudden increase in the level of regulatory capital on fiancial market stability.

In the Basel III framework, an additional term is added to the formula of the Basel II framework: the stressed Value-at-Risk. It is calculated in the same way as the usual Value-at-Risk measure. The only difference is the period used for its determination. This period is a "12-month period of significant financial stress" (BCBS 2009) for the stressed Value-at-Risk. Hence, it is a renunciation of the principle of assessing the risk situation of the last couple of trading days and calculating the level of regulatory capital for market risk based upon it. It requires effort to give periods that cause significant problems to financial institutions more weight in the calculation of the level of regulatory capital for

[1] published in *Quantitative Finance*, Vol. 10, No. 10, December 2010, pp. 1215-1224
[2] published in the *European Physical Journal B*, Vol. 73, No. 1 (2010), pp. 29-40

market risk. The new formula is as follows

$$\begin{aligned} \mathrm{cr}_t = \max\left(\frac{h}{60}\sum_{i=1}^{60}\mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t)\right) + \\ \max\left(\frac{h}{60}\sum_{i=1}^{60}\mathrm{sVaR}_{0.99}(\mathbf{10}|t-i), \mathrm{sVaR}_{0.99}(\mathbf{10}|t)\right), \end{aligned} \tag{2}$$

where sVaR is the stressed Value-at-Risk (the terms are interpreted in the same way as in Formula (1), albeit here for the stressed Value-at-Risk). However, the Basel III framework does not only change the level of regulatory capital for market risk associated with the assets held by a financial institute. It additionally raises the level of **minimum** capital requirements a financial institute has to hold independently of its actual assets. Although the increase in minimum capital requirements especially leads to a better capitalization of banks to sustain threats of credit risk, it is coordinated to all risk types. As described above, the overall level of regulatory capital consists of the sum of the regulatory capital of credit, market, and operational risk (BCBS 2006, 2010a/b, 2011a/b). Hence, we have to incorporate this increase in the minimum level of regulatory capital into a model juxtaposing the effects of the Basel II and Basel III framework, as undertaken in the third paper of the thesis, entitled *Does Basel III improve financial market stability? - A comparison with the Basel II framework*.

Four instruments introduced by the BCBS with the Basel III framework strengthen the capitalization of banks to help them survive in a critical financial environment. In addition to the previously mentioned stressed Value-at-Risk which is directly connected to market risk, there are two instruments suggested to raise the minimum level of regulatory capital. The first instrument is the capital conservation buffer, which is a constant that raises the actual level of regulatory capital step by step between 2013 and 2019 by 35%. On top of this increase, a countercyclical buffer can be built up in good times and released in bad times by the national regulatory authority. The countercyclical buffer can be no higher than the capital conservation buffer. It should guarantee that financial institution have enough minimum capital requirements to keep interbank lending up in bad times. Additionally, it is interesting to note how financial market stability is affected by the stepwise raise between 2013 and 2019. Ultimately, these are sudden changes in the minimum capital requirements once every year. Will these changes lead to shocks on the financial market? The *Effects of the new capital requirements of Basel III on financial market stability* are finally discussed in the fourth paper.

2 Methodology, results, and novel aspects of the four publications

In the following, we discuss the main goals and results of each paper. In addition to describing which scientific methods are used to obtain our results, we will show how the results of the papers are interrelated.

2.1 The impact of choice of VaR models on the level of regulatory capital according to Basel II

This paper deals with the choice of an appropriate Value-at-Risk model by a financial institution. A recent strand of academic (especially statistics-oriented) research is to develop methods which improve the estimation of the 1-step Value-at-Risk. For this purpose, different variations of GARCH models, neural networks or a wide range of distributions which can replicate fat tails are used (Alexander 2001). However, empirical studies reveal that financial institutions still use Value-at-Risk models with questionable assumptions (Homburg & Scherpereel 2005). One reason for this could be that they are easy to comprehend and implement (McNeil et al. 2005). However, does this prevent a financial institution from using a more sophisticated model if it can save funds due to a lower level of regulatory capital with their use? Without doubt, a financial institution saves funds with a lower level of regulatory capital since regulatory capital, especially common equity, is more expensive for them than loan capital (Holton 2003). The question is therefore: which Value-at-Risk model leads to a low level of regulatory capital.

In our empirical analysis, we have to face another problem which is often neglected when new Value-at-Risk estimators are proposed for use in the Basel II framework. We need the 1-step Value-at-Risk for the backtesting procedure. To calculate the level of regulatory capital for market risk, we need the 10-step Value-at-Risk (cp. Formula (1)) for which the 10-step return and loss distribution is required. For this purpose, we have to face the problem that the additivity property for i.i.d. distributed returns is necessary. The additivity property is only fulfilled for normal (due to the central limit theorem) and stable (due to the generalized central limit theorem) i.i.d. random variates (Rachev et al. 2003, 2007). We test for time series based on given underlying return distributions how accurate the Value-at-Risk estimators are for different Value-at-Risk models. Here, we choose both Value-at-Risk models with simple and more sophisticated underlying assumptions. Thereafter, we calculate the level of regulatory capital of market risk for these models.

The analysis reveals that a precise working model and a low level of regulatory capital are trade-offs. Models with questionable assumptions assuming the normal distribution for the return distribution and an equal weighting of past observations lead to significantly lower regulatory capital. Hence, financial institutions have no incentive to implement more sophisticated models in line with actual academic research since they would incur greater expenditure.

2.2 Does Basel II destabilize financial markets? - An agent-based financial market perspective

In this paper, we focus on the consequences of the Basel II framework for a financial market. Since Basel II has not been implemented for long or not at all in many countries, there is no empirical data available to answer this question. We have to come up with other solutions.

One possibility is to use heterogeneous agent models. These models have proven to be a powerful tool in many areas of economic policy, such as the analysis of the Tobin tax or central bank interventions (Westerhoff/Dieci 2006; Mannaro et al. 2008; Westerhoff 2003). Jean-Claude Trichet also assesses them as a reasonable alternative to existing economic and financial models. "Policy-makers need to have input from various theoretical perspectives and from a range of empirical approaches. Open debate and a diversity of views must be cultivated - admittedly not always an easy task in an institution such as a central bank. We do not need to throw out our DSGE [dynamic stochastic general equilibrium] and asset-pricing models: rather we need to develop complementary tools to improve the robustness of our overall framework. [...] First, we have to think about how to characterise the homo economicus at the heart of any model. The atomistic, optimising agents underlying existing models do not capture behaviour during a crisis period. We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices. Behavioural economics draws on psychology to explain decisions made in crisis circumstances. Agent-based modelling dispenses with the optimisation assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention," Trichet 2010.

We use a heterogeneous agent model developed by Lux and Marchesi (1999, 2000), in which we implement the regulations of the Basel II framework. In Lux and Marchesi's model, we have different traders interacting with one another who use different trading rules. Expressed in simplified terms, some rely more on the current price trend (chartists) whilst others expect the price to revert to its fundamental value (fundamentalists). To these groups, we add a group of regulated traders that only becomes active if regulations force them to do so. To be more precise, the agents in the model always believe in the chartists' and fundamentalists' trading rules, and only become forced to be active if a backtesting exception occurs.

When a backtesting exception occurs, the Value-at-Risk measure increases, as does multiplier h often, too (cp. Formula (1)). This leads to higher regulatory capital above the minimum required level of regulatory capital for the financial institution. To avoid additional expenditure by acquiring new regulatory capital, a financial institution sells risky assets. The higher the loss associated with the present Value-at-Risk level, the more risky assets are sold. Since we aim to draw a realistic picture of a financial institution's activities, we use the three Value-at-Risk models mainly used in practice. As we know from the first paper of this dissertation, financial institutions have strong intentions to behave in this way.

We find that the financial market is destabilized by the presence of regulations. The more agents are regulated, the higher the degree of destabilization is measured by volatility, distortion and the Hill tail index. In particular, the presence of extraordinary profits and losses increases. This is the opposite of what the BCBS wanted to achieve with the Basel II framework. The BCBS's intention was for financial institutions to withstand periods with extraordinary losses. But these very losses increase in the analysis conducted by our model.

2.3 Does Basel III improve financial market stability? - A comparison with the Basel II framework

After analyzing the Basel II framework, it stands to reason to analyze whether the changes undertaken in the Basel III framework lead to stabilization. For this purpose, we use a heterogeneous agent model based on the Discrete Choice Approach of Brock and Hommes (1998) and the adjustments of Franke and Westerhoff (2011). This is also a model with interacting chartists and fundamentalists.

Again, we incorporate regulated traders into this model. However, unlike in the previous paper, we do not use backtesting exceptions for the trading signal for three reasons. Firstly, it is more straightforward to use the level of regulatory capital directly: a financial institution will link its trading behavior more to the direct outcome of the calculation, hence the level of regulatory capital, than to the different terms included in its calculation. Secondly, the new formula for calculating regulatory capital for market risk within the Basel III framework does not rely completely on the most recent period – the period in which the backtesting exception occurred. The reason for this is the additional period used to calculate the stressed Value-at-Risk (cp. Formula (2)). Whereas in the previous formula an increase in h was in line with an increase in the VaR in Basel II, in Basel III a backtesting exception does not necessarily – or rather quite seldom – causes an increase in the sVaR due to the different periods considered for calculating VaR and sVaR. Thirdly, we have to compare the level of regulatory capital with the other new instruments of the Basel III framework, hence the increased minimum level of regulatory capital. For this purpose, we need a common standard of comparison to incorporate this change into the model, too. Here, the level of regulatory capital is applicable; backtesting exceptions are not applicable.

The analysis is carried out for both Basel II and Basel III frameworks. The Basel III framework has a significantly higher impact on the model's dynamics than the Basel II framework. The Basel III framework stabilizes the financial market if the regulations are used in a moderate manner. If the financial market is regulated too severely, meaning a high proportion of traders are suddenly affected by regulations, very severe crashes may occur due to the considerable influence of the regulated traders' sales.

2.4 Effects of the new capital requirements of Basel III on financial market stability

After comparing the former Basel II and the new Basel III framework, it is important to scrutinize the function of the newly proposed instruments in the Basel III framework. To this end, all changes are implemented in the heterogeneous agent model used in the previous paper. By doing so, we can test the influence of each of the proposed instruments – stressed Value-at-Risk, capital conservation buffer and the countercyclical buffer – and whether the transition period has an impact on financial market stability. We can explore these instruments implemented together or we can "switch off" one or more instruments to extract the exclusive effect of one instrument.

The increase in the level of regulatory capital for market risk by adjusting the calculation directly based on assets held by the regulated financial institution is quite promising, as the Monte Carlo simulation conducted reveals. The stressed Value-at-Risk has a stabilizing effect. In contrast, the general increase in minimum capital requirements for all risk types of the framework leads to a destabilization of the financial market for both the capital conservation buffer and the countercyclical buffer. The transition period has no significant effect on financial market stability. Regulations leading directly to the respective risk type, dependent on the risk coordinated to assets held by the financial institution, seem to be more promising than a general increase in minimum capital requirements for financial market regulation.

The next section concludes by comparing the results of the four papers and suggesting possibilities for further research.

3 Lessons from the four papers

The goal was to identify, measure and draw possible consequences from the impact of Basel II/III regulations. For the Basel II framework, we identified that accurate Value-at-Risk estimators cause a significantly higher level of regulatory capital. This might prevent financial institutions from implementing them.

Incorporating the Basel II regulations into heterogenous agent models gives us an impression of their impact. We find that the higher the proportion of regulated agents in the financial market, the more extraordinary profits and losses occur and the higher the volatility – destabilization occurs. This problem seems to be solved by implementing the Basel III framework. For low and medium proportions of regulated traders, we obtain a stabilization of the financial market. However, special situations and conditions may lead to severe crashes for high fractions of regulated traders which are even worse than those identified in the previous analysis of the Basel II framework. Both analyses reveal that only responsible use to a moderate extent leads to the regulations having a positive effect. Excess regulation may cause the opposite of the regulation's intent to occur. This aspect is reinforced by the next paper. The precisely defined stressed Value-at-Risk clearly aiming at the regulation of financial markets due to its influence on market risk has a stabilizing effect, whereas general regulations, such as the capital conservation buffer and the countercyclical buffer, fail to increase financial market stability.

The challenges for further research are widespread. One aspect could be to improve the models' accuracy by undertaking additional empirical work. Better knowledge of how many traders are affected by regulations on every trading day and the amount of their respective excess demand would improve the models. It would help to identify critical moments at which agents are regulated too strongly to avoid crashes, as identified in the second and third paper, especially for large proportions of regulated traders generating high absolute excess demand.

In this thesis, we focused on a financial market context. If the capital conservation buffer and the countercyclical buffer are able to maintain interbank lending, it may be acceptable for them to have a (slight) destabilizing impact on financial market stability. Here, we need models that can connect credit to market risk to obtain a comprehensive impression of the whole impact of the Basel frameworks. Another approach could be to test whether regulations aiming directly at credit risk are perhaps a better way of stabilizing markets than increasing minimum capital requirements. A similar procedure comparable to the stabilizing influence of the stressed Value-at-Risk in the fourth paper might be a solution.

The next approach concerns Value-at-Risk models and the implementation of more sophisticated models. Here, adjustments to the calculation formula may create financial incentives for their use. If more sophisticated models lead to a low level of regulatory capital, financial institutions may promote their implementation. A new definition of factor h could achieve this goal. It could increased if the Value-at-Risk model fails to meet specific stylized facts of financial time series, instead of using the backtesting method. In this context, it could also be tested whether sophisticated models do indeed lead to greater financial stability in an agent-based financial market.

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The impact of the choice of VaR models on the level of regulatory capital according to Basel II*

Oliver Hermsen†

Abstract

The Basel II framework allows the calculation of the capital requirements for market risk with Value-at-Risk models. Since no special model is prescribed in the framework, banks may use simple models with questionable assumptions concerning their underlying distributions. Our numerical analysis reveals that simple VaR models that perform noticeably worse than comparable simple models with more realistic assumptions may lead to a lower level of regulatory capital for banks. For this reason, banks have a major incentive to implement bad models. This is obviously contrary to the interests of regulatory authorities.

Keywords: Value-at-Risk models, Basel II, numerical analysis, level of regulatory capital, bank regulation

JEL Classification:

G32 - Financial Risk and Risk Management; G38 - Government Policy and Regulation

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`http://www.tandfonline.com/doi/abs/10.1080/14697680903419701`

1 Introduction

The goal of this paper is to show that capital requirements for market risk according to the Basel II regulatory framework may be higher for models that estimate the VaR more precisely than others. If this is the case, banks may be prevented from implementing models that capture risk more accurately.

The "International Convergence of Capital Measurement and Capital Standards" (Basel II) allows the calculation of the capital requirements for market risk by means of a Value-at-Risk (VaR) model when performing the Internal Models Approach. However, the Basel Committee for Banking and Supervision (BCBS) does not prescribe banks a special type of model (BCBS, 2006, D.4.(f)). In the literature, many models that determine the VaR and, thus, the capital requirements for market risk are described. These VaR models differ mainly in how carefully they model stylized facts of return series.

In this paper we consider five VaR approaches with different distributional assumptions. Many VaR approaches frequently used in practice, such as the historical volatility and Exponential Weighted Moving Average (EWMA) approach, still assume normal distribution (Pafka et al. (2001) and Bormetti et al. (2007)), although Fama (1965) and Mandelbrot (1963) questioned this assumption long ago. One argument for the use of these models is often that they are easy to understand and implement. Other models try to characterize the distribution of returns with more realistic distributions, such as the student-t distribution, the Generalized Error Distribution (GED) or the stable distribution (to comprehend potential distributions to model fat tails see Paolella (1999), Alexander (2001), Mattedi et al. (2004), Rachev et al. (2005) and Bormetti et al. (2007)), since these distributions are able to match the fat tail property of the return distribution quite well.

With the stable parameters and Stable Exponential Weighted Moving Average (SEWMA) approach we therefore also incorporate VaR methods where the normal distribution is replaced by the stable distribution, unlike in the historical volatility and EWMA approach (Ortobelli et al. (2004) and Rachev et al. (2005)). The advantage of being able to comprehend and implement these models easily, essential in practice, is not impaired substantially by this modification.

The fifth VaR approach that is also sometimes used in practice is the historical simulation. Here, we use the quite realistic empirical distribution of equally weighted historical price changes to determine the VaR. The problems involved in this approach are dependence on the history of data and a higher computational complexity (Bormetti et al., 2007).

Up to now, it is not known which of these assumptions describe the "right" unconditional return and loss function (Bradley and Taqu, 2003). An additional problem is that Basel II stipulates the one-step distribution for daily returns or losses and the ten-step distribution for cumulative returns or losses for a time horizon of ten days. Both aspects should therefore be determined adequately by the VaR approach.

Volatility clusters and time dependence in return series are the next problems that hamper determination of the unconditional return distribution. It is therefore difficult to test which distributional assumptions concerning the unconditional distribution fit best. Such an unconditional return distribution more or less presumes that volatility is constant over time (Alexander, 2001).

Which model will a bank choose to determine its capital requirements? Banks strive to keep capital requirements low, since it is more expensive to acquire regulatory capital compared to loan capital. A bank may thus prefer models that involve low capital requirements and that are accepted by the supervisory authority at the same time.

In contrast to these aims, the supervisory authority strives to reach a high level of capital requirements. Some reasons for this are that a bank suffering from difficulties due to low capital requirements may cast a damning light on the whole financial sector. This can create a domino effect, causing the whole financial sector to get into difficulties (Crouhy et al., 2006). In fact, the current financial crisis shows us quite plainly how the world economy can be negatively influenced by bank troubles or even bank failure.

In this paper, we numerically investigate how the different VaR models perform in determining quantiles of unconditional return and loss distributions, respectively. Furthermore, the consequences of these results for the determination of regulatory capital are explored. From the point of view of the regulatory authority, it would be desirable for the models to capture the risk adequately, causing a lower level of regulatory capital compared to these models that perform badly, so that there is an incentive for banks to implement well-performing models. In this case, the targets of not only the banks but also the supervisory authority would be achieved. The novel aspect of this paper is that the numerical analysis provides evidence that the opposite seems to hold true. We find that banks benefit from the use of poor performing models, although backtesting should ascertain the adequacy of VaR models, causing the incentives of the regulatory authority to be undermined.

The next section highlights important aspects of determining the level of regulatory capital for market risk (lrc) and provides a brief description of the investigated VaR models. Subsequently, the numerical analysis procedure is introduced. The findings of the analysis and their consequences are then discussed in detail. The final section concludes the paper and offers suggestions for future research.

2 Value-at-Risk models

The next section is organized as follows. In the first subsection, we define the VaR. We then explain how the level of regulatory capital for the market risk is determined according to the BCBS and illuminate the implications connected with this formula. Finally, we briefly describe the chosen VaR models.

2.1 Definition of VaR

Before presenting the models, we will first explain how the VaR is defined in this paper. The loss distribution for period τ is defined as

$$L_{\tau|t} := -\left(V(t+\tau) - V(t)\right), \tag{1}$$

where $V(t)$ is the value of the portfolio at time t. Accordingly, the loss function indicates the change in the value of the portfolio between period t and $t+\tau$.

The VaR for a level of significance $1-\alpha$ is then defined as the smallest number $l_{1-\alpha}(\boldsymbol{\tau}|t)$ for which the probability of exceeding $l_{1-\alpha}(\boldsymbol{\tau}|t)$ is not higher than $1-\alpha$. According to McNeil et al. (2005) and Jorion (2007), we can write:

$$
\begin{aligned}
P\left(L_{\boldsymbol{\tau}|t} \leq l_{1-\alpha}(\boldsymbol{\tau}|t)\right) = 1-\alpha \leftrightarrow \\
P\left(L_{\boldsymbol{\tau}|t} \leq \mathrm{VaR}_{\alpha}(\boldsymbol{\tau}|t)\right) = 1-\alpha \leftrightarrow \\
P\left(V(t) - V(t+\tau) \leq \mathrm{VaR}_{\alpha}(\boldsymbol{\tau}|t)\right) = 1-\alpha.
\end{aligned} \tag{2}
$$

Often, the VaR is calculated via the return distribution $Y_{\boldsymbol{\tau}|t}$, which is defined as

$$
Y_{\boldsymbol{\tau}|t} = \ln\left(\frac{V(t+\tau)}{V(t)}\right) = Y_{t+1} + Y_{t+2} + \ldots + Y_{t+\tau} \tag{3}
$$

with $Y_t = \ln\left(V(t)/V(t-1)\right) = \ln(V(t)) - \ln(V(t-1))$. The τ-step return distribution $Y_{\boldsymbol{\tau}|t}$ depends on the information known at time t. From (3), it follows for the portfolio value $V(t+\tau)$, according to Reiss and Thomas (2007),

$$
V(t+\tau) = V(t)\exp(Y_{\boldsymbol{\tau}|t}). \tag{4}
$$

The determination of $\mathrm{VaR}_{\alpha}(\boldsymbol{\tau}|t)$ with $Y_{\boldsymbol{\tau}|t}$ can then be realized as follows. When we describe the α-quantile of $Y_{\boldsymbol{\tau}|t}$ with $Q_{\alpha}(\boldsymbol{\tau}|t)$, we obtain

$$
\begin{aligned}
P\left(Y_{\boldsymbol{\tau}|t} \leq Q_{\alpha}(\boldsymbol{\tau}|t)\right) = \alpha \leftrightarrow \\
P\left(\ln\left(\frac{V(t+\tau)}{V(t)}\right) \leq Q_{\alpha}(\boldsymbol{\tau}|t)\right) = \alpha \leftrightarrow \\
P\left(V(t+\tau) \leq V(t)\exp(Q_{\alpha}(\boldsymbol{\tau}|t))\right) = \alpha.
\end{aligned} \tag{5}
$$

Now, from equations (2) and (5) it follows that $V(t) - \mathrm{VaR}_{\alpha}(\tau|t) = V(t)\exp(Q_{\alpha}(\tau|t))$ and hence:

$$
\mathrm{VaR}_{\alpha}(\boldsymbol{\tau}|t) = V(t)\left(1 - \exp\left((Q_{\alpha}(\boldsymbol{\tau}|t)\right)\right). \tag{6}
$$

The aim of the VaR approaches in this paper is to determine $Q_{\alpha}(\boldsymbol{\tau}|t)$ to calculate the VaR via (6).

2.2 The level of regulatory capital

The BCBS (2006, 718 (LXXVI) (i)) prescribes the following formula for the calculation of regulatory capital for market risk:

$$\mathrm{lrc}_{1|t} = \max\left(\frac{h}{60}\sum_{i=1}^{60}\mathrm{VaR}_{0.01}(\mathbf{10}|t-i), \mathrm{VaR}_{0.01}(\mathbf{10}|t)\right), \tag{7}$$

where $\mathrm{lrc}_{1|t}$ is the level of regulatory capital in the next period, $\mathrm{VaR}_{0.01}(\mathbf{10}|t-i)$ is the VaR with $\alpha = 0.01$ of the loss distribution 10 periods (days) ahead (which can easily be calculated with (6) from the return distribution), and h is a multiplication factor or multiplier. The multiplier ranges between $h = 3$ and $h = 4$. The bank or supervisory authority has to evaluate whether a VaR model is applicable to capture risk by means of a backtesting procedure based on $\mathrm{VaR}_{0.01}(1|t)$. If there are problems concerning the adequacy of the model, the factor h is raised up to a level of $h = 4$. At this level, the supervisory authority can force the bank to change its approach of calculating VaR (it is then assigned to the red zone (rz)).

At this point, Danielsson et al. (1998) recognized the problem that an accurate estimation of the one-step VaR, and hence having no complaints concerning the model in the backtesting procedure, do not necessarily lead to an accurate ten-step VaR estimator. The square root of time rule might lead to an underestimation of $\mathrm{VaR}_{0.01}(\mathbf{10}|t)$ in this context and thus to an underestimation of $\mathrm{lrc}_{1|t}$. The multiplication factor aims to correct this problem.

However, it is quite difficult to test whether the ten-step distribution is determined correctly. Due to the central limit theorem, it is not possible to determine the correct theoretical ten-step distribution for any distribution with a finite mean and variance (except for the normal distribution, of course). In recent years, the stable distribution has been put forward as a solution to this problem by many researchers (e.g. Rachev et al., 2007; Nolan, 2003; Mittnik et al., 2002). The advantage, besides its ability to match the observed fat tails of unconditional return distributions, is that it fulfills the additivity property since its variance is infinite for $1 < \alpha < 2$, and therefore the generalized central limit theorem applies (Nolan, 2003).

The stable distribution can be characterized by stability parameter $\alpha \in (0, 2]$, skewness parameter $\beta \in [-1, 1]$, scaling parameter $\delta > 0$ and location parameter $\mu \in \mathbb{R}$. The additivity property implies that a sum of i.i.d. stable distributed returns is also stable distributed. This makes this distribution especially interesting for its application in the VaR models presented below, since the accurate modelling of the ten-step distribution is of major importance to determine an adequate estimator for the level of regulatory capital (cp. (7)).

In the following, we describe and juxtapose the VaR approaches used for numerical analysis. They differ mainly in two aspects. The first aspect is the distribution of the residuals. Here we assume a normal distribution for the historical volatility and the EWMA approach (later referred to as "normal approaches"), which are frequently used in practice. In the stable parameters and SEWMA approaches (later referred to as "stable approaches"), we replace the normal distribution by the above-described stable distribution. For the historical simulation approach we use the empirical distribution of the residuals.

The second aspect is the weighting of historical observations for the variance estimation. Here, historical volatility, historical simulation and stable parameters weight every observation the same, whereas EWMA and SEWMA weight recent observations higher.

Table 1 provides a formal description of these VaR approaches with one- and τ-step quantile estimators and literature stating where more detailed descriptions can be found. In the following analysis of the next subchapters, we focus on the different underlying residual distribution of the VaR approaches, which can be found in column 3 of this table. Using this residual distribution, we can easily suggest the return or loss distribution with the model defined in column 2.

Table 1 comes about here

3 Methodology

The underlying return distribution is a factor that significantly influences the estimation of extraordinary losses or gains, since they are determined by the distributions' 1% quantile. Remember that these quantiles are the basis for calculating the level of regulatory capital (see (7)). It is therefore quite important to investigate and juxtapose the differences in the lrc resulting from varying underlying distributions in the approaches and connected with this point from an under- or overestimation of the corresponding 1% quantile by choosing a special VaR approach.

Studies exploring real data often conclude that normal approaches do not capture the risk as adequately as models based on fat tailed distributions, such as the stable approaches (cp. e.g. Nolan, 2003; Mittnik et al., 2002). Since real data shows stylized facts such as volatility clustering, it is problematic to assume a special distribution for the considered time horizon. In this numerical analysis, we focus especially on the consequences of a problematic distributional assumption in the VaR model. We choose i.i.d. random variables and exclude volatility clusters to test whether the quantile of the unconditional return distribution is accurately determined by the VaR model and to explore the consequences for the determination of the level of regulatory capital. Thus, it is possible to analyze the impact of the underlying distribution.

We start our numerical analysis by simulating time series with i.i.d. random variables. The i.i.d. random variables have four different underlying **given distributions** for the return distribution, namely the normal, stable, skewed student-t, and GED distribution (as previously stated, an adaption from $Q_\alpha(\boldsymbol{\tau}|t)$ to $\mathrm{VaR}_\alpha(\boldsymbol{\tau}|t)$ can easily be carried out by (6)). The parameters of the normal distribution (μ, σ), the stable distribution (α, β, δ, μ), the skewed student-t distribution (μ, σ, ν and ξ) and the GED (μ, b^2, γ), which can be found in Table 2, are estimated from the DAX series from 08-20-1995 to 06-29-2007. The maximum likelihood estimator for every distribution is chosen. By carrying out the analysis, the theoretical quantile ($Q^{\mathrm{theo}}_{\alpha,\tau}$) of the unconditional time series is **known** and can be compared with the estimates of the VaR models (Q_α). Note that the theoretical 1%-quantile of the different distributions differs significantly from $Q^{\mathrm{theo}}_{0.01,1} = -0.0535$ for the stable distribution to $Q^{\text{theo}}_{0.01,1} = -0.0362$ for the normal distribution (see Table 2).

Table 2 comes about here

There is an additional advantage choosing this approach, referring to the aforementioned properties of stable distributions. Whereas the backtesting exceptions are determined by the one-step VaR, the regulatory capital is determined by the ten-step VaR in the Basel II framework. Both the normal and the stable distribution are the only distributions that fulfill the additivity property (Rachev et al., 2003; Rachev et al., 2007). Due to this property, the 1%-quantile of the ten-step return distribution can also be determined exactly with $Q^{\text{theo}}_{0.01,10} = -0.2150$ for the stable and $Q^{\text{theo}}_{0.01,10} = -0.1132$ for the normal distribution. It can also be tested whether the VaR models determine it adequately.

Since it is obvious that the historical volatility approach will determine the theoretical quantile for the time series with normal random variables, and vice versa, the stable parameters approach will determine it for the time series with stable random variables (hereinafter referred to as normal and stable time series), we also consider two other alternatives with the skewed student-t distribution and GED. This way, the performance of the VaR approaches can be determined without implying one of the distributional assumptions (normal or stable distribution) in advance. Of course, no exact determination of the ten-step distribution for these distributions is possible, since they do not have the additivity property.

The gap between the theoretical and estimated quantile estimator should be as small as possible. With a p-test it is tested to a significance level of $a = 0.1$ (with the critical niveau of $p_{crit,1-a=0.9}$) and $a = 0.01$ (with the critical niveau $p_{crit,0.99}$), respectively, if the estimator predicts the theoretical estimator acceptably. The results of the different simulated time series are presented in the next sections. The above-mentioned problems, which may occur if banks do not hold an adequate level of regulatory capital, make allowances for adopting a one-sided test, which denounce an overestimation of the 1%-quantile of the return distribution [1]. Since $n = 1705$ values are incorporated, the test

[1] The hypothesis $p \leq Q^{\text{theo}}_{\alpha}$ is tested against the alternative hypothesis $p > Q^{\text{theo}}_{\alpha}$. The hypothesis is rejected, if $T = \frac{Q_\alpha - Q^{\text{theo}}_{\alpha}}{\sqrt{Q_\alpha(1-Q_\alpha)}}\sqrt{n} \in [p_{crit;1-a}; \infty)$.

performance is acceptable - apart from the usual problems that occur when testing for small probabilities.

We obtain the 1705 values by executing the following procedure, called rolling analysis. It is assumed we have 3000 ordered data values. With the first $w = 1000$ values (which will be called window length w from now on), we obtain a first one-step VaR estimator. The first data value is then excluded and the 1001st is included in the analysis for the second one-step VaR estimate. This procedure continues until the 1001st and 3000th data value provide an estimation. With these 2000 one-step VaR estimates we obviously obtain 1990 ten-step VaR estimates. Since the BCBS postulates carrying out the backtesting procedure (and hence the determination of h in (7)) with estimates from one year (these are four complete quarters), the number of values shrinks to 1705.

Depending on the VaR method, the length of w provides different results. E.g. a longer window length has the consequence that the estimators of the parameters of the stable distribution in the SEWMA model differ slightly. In turn, this also leads to minor discrepancies concerning the quantile estimators of both the one- and ten-step distribution.

Before presenting the results of this analysis, it is necessary to add a remark. Of course, the EWMA and SEWMA models are especially designed to capture clustered volatility. It can therefore be assumed before commencing this analysis that they perform worse than other models, since there are no volatility clusters in the time series considered. However, comparing their estimators is quite relevant for two reasons.

First, a model should also perform well if the risk situation is relatively stable for a certain time period (e.g. $w = 250$) and no volatility clusters occur. Recent research shows that the assumption of periods with stable mean and variance is quite realistic. Some models work explicitly with this assumption to assume a normal distribution with varying parameters for each of those stable periods (Bormetti et al., 2008). Secondly, the underlying distributions are the normal and stable distribution, respectively. This way, it is possible to juxtapose and compare the results in another context other than that taken by the historical volatility and stable parameters approach.

To achieve a high degree of generalization, the analysis is performed 1000 times for each model and window length.

4 Results

Our results are summarized in Tables 3 and 4 of this section. Note that "area B" specifies how many of the estimators exceed the critical value of $p_{crit,0.90}$. Analogously, "area A" states the percentile exceeding even a critical niveau of $p_{crit,0.99}$. If too many estimators are located in these two areas, the reliability of average potential good results declines. This means in fact that the method provides good results on average, but that in many cases the risk situation is underestimated. A model predicting the theoretical quantile that is appropriate in the mean but often underestimates it for only small deviations remains problematic.

Table 3 proceeds with the same results for the ten-step distribution. The last three columns show the ratio of how often the supervisory authority would have the right to reject the model, since the red zone was reached (rz). Then the average of the multiplication factor h is given (∅ multi). The last column shows the average level of regulatory capital (∅ lrc).

4.1 Time series with the additivity property

As previously mentioned for normal and stable time series, it is possible to juxtapose not only the estimators of the one-step-quantile with the theoretical quantile. Due to the additivity property, we can also determine the ten-step-quantile estimator with the respective theoretical quantile of the ten-step distribution. We identify severe weaknesses of the considered VaR approaches, especially for the quantile estimators of the ten-step distribution.

First, we analyze the normal time series (upper part of Table 3). Whereas the one-step quantile estimators are quite accurate without strong deviations (apart from the historical simulation approach), there are higher deviations for the quantile estimators of the 10-step distribution. Here the historical volatility (for both window lengths) and again the historical simulation provide bad results. This is puzzling since especially the assumptions of the historical volatility fit perfectly to the simulated time series. The level of capital requirements is quite similar for the historical simulation, historical volatility, and EWMA approach.

Table 3 comes about here

The stable approaches overestimate the theoretical quantile in most cases (cp. the four bottom lines of the upper part of Table 3). It is therefore not surprising that the lrc is higher for those two approaches, although the average level of the multiplication factor is lower. The ten-step distribution seems to be more relevant here for the calculation of the lrc.

We now compare these results with those for the stable time series from the bottom part of Table 3. Remember that this return distribution has fat tails, in contrast to the previously considered normal time series. With the implementation of this more realistic assumption concerning the underlying return distribution, the performance of most considered VaR approaches declines dramatically. Surprisingly, this leads to quite low levels of regulatory capital for badly performing approaches. In the following, we will have a closer look at some of the results in Table 3 that support this observation.

Comparing the average level of regulatory capital (last column of Table 3) of the various methods, the discrepancy becomes much higher. The lowest level is achieved for the EWMA approach - the approach that performs the worst concerning the accuracy of the quantile estimators. Table 3 (row three of the bottom part) reveals the following facts: the approach can be rejected by the supervisory authority for only 27% of the simulated time series (rz), although 51.2% of the estimators are in area B. The problem becomes apparent when we look at the ten-step distribution (remember: this distribution is relevant when calculating the level of regulatory capital). 88.6% of the estimators are in area B and even 80.5% are in area A. This problem does not only occur in the EWMA approach. All methods, with the exception of the stable parameters approach, underestimate the quantile of the ten-step distribution noticeably. Here, it is remarkable that the regulation authority can only reject a significantly smaller proportion (cp. Table 3 for the exact values). The lrc is only half as high as in the good performing stable parameters approach, especially for the historical volatility and historical simulation. So far, it seems that a low lrc does not necessarily correspond to a good performing method.

The approach that corresponds best to the risk situation is the stable parameters approach, which is not surprising, since its properties exactly fit the properties of this time series. For both window lengths, on average, the quantile estimator is accurate for the one- and ten-step distribution. Despite these facts, the lrc reaches a level of 62.48% - about 30% more than for the badly performing historical volatility approach. It becomes apparent that a higher level of the multiplication factor of the normal approaches cannot correct the underestimation of the quantiles occurring in these approaches.

Similar results can be observed in the other approaches or window lengths, as shown in Table 3. It seems that the use of the ten-step distribution and the manner of increasing the multiplication factor by calculating the lrc leads to a lower level of the lrc for badly performing models, when the underlying unconditional return distribution is fat tailed and skewed. In the next subsection, this is observed for i.i.d. time series with random variables from a skewed student-t and GED distribution.

4.2 Time series without the additivity property

For the skewed student-t and GED time series we can only perform the analysis for the one-step distribution, due to the lack of the additivity property. As with the stable distribution, both unconditional return distributions exhibit fat tails. For this situation, some of the above-mentioned effects are emphasized. Mention must first be made of the fact that using badly performing models leads to a lower lrc for this setting again. Table 4 summarizes the results in the same way as demonstrated before.

Table 4 comes about here

What is most significant in Table 4 is the very bad performance of the VaR approaches, with an underlying normal distribution indicated by more than 75% of the estimators located in area A. For these, we reveal a quite low lrc of about 37% for the skewed student-t time series and 32% for the GED time series. These values seem to be too low when juxtaposed with the result for the normal distribution in the upper part of Table 3, where we obtain similar values. For the normal time series, these values are reliable on average, since the estimators for the 10-step quantiles are accurate on average, too. However, the theoretical quantiles for the one-step distribution of the unconditional return distributions of the skewed student-t and GED are considerably higher (see Table 2) indicating a higher risk of extraordinary profits and losses. This fact should result in a smaller quantile, not only for the one- but also for the ten-step distribution. The reason for these low values for the lrc might be an underestimation of the unknown quantile of the ten-step distribution in this context, as with the stable distribution in the previous subsection. The proportion of estimators located in A and B (see the bottom part of Table 3) increases considerably for the ten-step distribution, especially for historical volatility, EWMA and also for the historical simulation approach. This is probably also the reason for the low lrc for the historical simulation approach for the student-t and GED time series.

When looking at the skewed student-t time series, the other model that estimates the theoretical quantile quite well beside the historical simulation is the SEWMA approach. But the level of regulatory capital, at about 56%, is much higher for this. In connection with the results for the i.i.d. stable distributed time series (here, a similar result was obtained for the well-performing stable parameters approach), this result seems to be more realistic as the estimates here for the one- and ten-step distribution are comparably good. Again, for this scenario, it can be stated that badly performing models lead to a lower level of regulatory capital.

A closer look at the results for the GED time series (bottom parts of Table 4) clarifies that the stable approaches overestimate the quantile here, which leads to a very high level of regulatory capital. Since the lrc is even higher than for the stable distribution (see bottom part of Table 3), this seems to be as unrealistic as the underestimation for the other approaches. With regard to this result, it is important to mention that a considerably too high lrc also implicates negative consequences. If the lrc is significantly too high, there is more money is in the financial system. Accordingly, this increases the chance for bubbles and crashes to occur in financial markets.

We can therefore conclude that none of the considered approaches seem to estimate the lrc appropriately here. But again it is obvious that the use of badly performing models leads to a lower lrc.

Recapitulating the facts of this subsection, the normal approaches in particular perform quite badly, especially when the time series are generated from random variables of fat tailed and skewed distributions. Paradoxically, this does not lead to a higher level of regulatory capital compared to the stable approaches. These approaches adequately estimate the relevant 1%-quantile, especially for the ten-step distribution, which is decisive for the more precise calculation of regulatory capital. The second effect might be that the multiplier does not discriminate between well and badly performing models.

5 Conclusions

Several studies conclude that the unconditional return distribution is not normal distributed, and that volatility tends to cluster. However, the BCBS does not stipulate that banks use models in which these stylized facts are integrated. In this paper, we focused on the consequences of different ways of modeling the underlying return distribution. All approaches are easy to implement, so it is possible to use them in practice. It was revealed that the models with a poor predictive quality are those where there is no integration of realistic distributional assumptions. Models that try to characterize the fat tails of the unconditional return distribution provide much better results. However, banks still use models with unrealistic assumptions.

The sole reason might not only be the fact that they are easier to implement. The simulation study makes apparent that the spread of the multiplier between 3 and 4, as prescribed by the BCBS, does not separate adequately between well and badly performing models. A good predictive quality of the model and a low level of regulatory capital are trade offs - which cannot be the aim of the regulatory authority. It is understandable that banks strive to keep regulatory capital levels low. If it is possible to realize this aim with badly performing models they will do so or - expressed more drastically - the use of models with more realistic underlying distributional assumptions seems to be "punished" with a higher level of regulatory capital. The consequence seems to be that banks have little interest in implementing better performing approaches.

Adjusting the expression for calculating regulatory capital (equation (7)) might be a possible solution. Hereby, we should bear in mind that the lrc is calculated adequately for the respective risk situation, meaning it should be not too low and not not high. A modification of the equation, which leads to a considerably higher lrc, may have negative implications for financial market stability, because more money in the system would increase the risk of financial bubbles and - of course - also crashes.

The first problem of the actual expression that became apparent in the results of the numerical analysis is the multiplication factor. This plays a decisive role in determining the regulatory capital, as it is iteratively raised up to a maximum of 4. First it is set to $h = 3$, even for models that consider stylized facts. If the backtesting procedure brings weaknesses forward, it will be raised. But it seems that this procedure favors badly performing methods over methods that estimate the quantile accurately. Bringing the aims of the BCBS and the supervisory authorities back to mind, this cannot be their target, since they are interested in an adequate estimation of risk. In contrast, the actual rule incentives the banks to apply methods with obvious drawbacks.

At this point, it is important to mention that the idea of using such a multiplier is not bad. Many smaller institutions may have problems in implementing sophisticated models, such as GARCH models. However, the spread of the multiplier might be raised so that the implementation of more sophisticated models is honored, whereas banks with simple models have to suffer from a higher level of regulatory capital. Determining an adequate spread to reach this goal could be the subject of further research. The models presented in this paper as alternatives to the normal approaches are not very difficult to implement, since only one distribution is changed. For this reason, smaller institutions should also be able to take advantage of them, meaning that an alignment of the multiplication factor could also lead to the implementation of more reliable models in smaller institutes.

The second problem of (7) is that the VaR is calculated based on the ten-step VaR distribution. As shown in the simulation study, a VaR model that performs well in estimating the theoretical quantile of the one-step distribution, might predict the theoretical quantile of the ten-step distribution very inadequately (cp. Tables 3 and 4). The backtesting procedure is based on the one-step distribution, which means that the judgement of whether a method is acceptable or not is based on another distribution than that one ultimately determining the level of regulatory capital. So this result is quite precarious, since an underestimation of the theoretical quantile in the ten-step distribution need not necessarily be identified by the backtesting procedure that should guarantee the adequacy of the method. This problem cannot be solved as easily as the determination of the multiplication factor. However, due to diversification, it might diminish when performing a multivariate analysis. The realization of the multivariate analysis in this context could also be the subject of further research.

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VaR Approach	Model Description	Residual Distribution	Quantile Estimation	Literature
Normal approaches				
Historical Volatility	$y_i = \mu + u_i$	$u_i = \sigma\epsilon_i$ $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$	$Q_\alpha(\boldsymbol{\tau}\vert t) = \tau\widehat{\mu} + z_\alpha\sqrt{\tau}\widehat{\sigma}$	BCBS (2006, 718 (LXXVI) (c) and (f)) Danielsson et al. (1998)
EWMA	$y_i = \mu + u_i$	$u_i = \sigma_i\epsilon_i;$ $h_{t+1} = (1-\lambda)u_t^2 + \lambda h_t$ $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1);\ \lambda = 0.94$	$Q_\alpha(\boldsymbol{\tau}\vert t) = z_\alpha\sqrt{\tau\widehat{h}_{1\vert t}}$	Zangari (1996) Holton (2003)
Simulation approach				
Historical Simulation	One-step: $\{y_i\}_{i=1}^n$ τ-step: $\widetilde{y}_{j,t+\boldsymbol{\tau}} = \sum_{k=1}^{\tau}\widetilde{y}_{j,t+k}$, with τ series of $\{\widetilde{y}_i\}_{i=1}^n$ $j = 1,\ldots,5000$	Empirical	One-step: $Q_\alpha(1\vert t) = \widehat{q}_\alpha(\{y_i\})$ τ-step: $Q_\alpha(\boldsymbol{\tau}\vert t) = \widehat{q}_\alpha(\{\widetilde{y}_i\})$	McNeil et al. (2004)
Stable approaches				
Stable Parameters	$\widetilde{z}_i = u_i$	$u_i = \delta\epsilon_i$ $\epsilon_i \overset{i.i.d.}{\sim} S(\alpha,\beta,1,0)$	$Q_\alpha(\boldsymbol{\tau}\vert t) = \kappa_{\alpha,\beta}\tau^{\frac{1}{\alpha}}\widehat{\delta}$	Mittnik et al. (2002) Rachev et al. (2003)
SEWMA	$\widetilde{z}_i = u_i$	$u_i = \delta_i\epsilon_i$ $\delta_{t+1}^{\nu} = (1-\lambda)\vert\widetilde{z}_t\vert^{\nu}A(\nu) + \lambda\delta_t^{\nu}$ $\epsilon_i \overset{\text{i.i.d.}}{\sim} S(\alpha,0,1,0);\ \lambda = 0.97$	$Q_\alpha(\boldsymbol{\tau}\vert t) = \kappa_\alpha\tau^{\frac{1}{\alpha}}\widehat{\delta}_{1\vert t}$	Ortobelli et al. (2004) Lamantia et al. (2004)

z_α: α-quantile of the normal distribution; $\kappa_{\alpha;(\beta)}$: α-quantile of the (asymmetric) stable distribution; $Q_\alpha(\boldsymbol{\tau}|t)$: α-quantile of the τ-step return distribution; $\{y_i\}_{i=1}^n$: series of returns; $\{\widetilde{y}_i\}_{i=1}^n$: series of randomized one step-returns; $\widehat{q}_\alpha(\{\widetilde{y}_i\})(\widehat{q}_\alpha(\{y_i\}))$: quantile of the (randomized drawn) returns; $\widetilde{z}$: centered returns; h_{t+1}/δ_{t+1}: Forcast for $t+1$ of the conditional variance/conditional scaling parameter

Table 1: Survey of Value-at-Risk approaches

Additional remarks: The calculation of VaR is realized with (6). For the quantile estimator of the EWMA approach, we assume the usual simplification $\mu = 0$. There is $A(\nu) = \frac{\Gamma\left(1-\frac{\nu}{2}\right)\sqrt{\pi}}{2^{\nu}\Gamma\left(1-\frac{\nu}{2}\right)\Gamma\left(\frac{\nu+1}{2}\right)}$ and $\nu \in (0,\alpha]$. For the estimation of ν see Samorodnidsky and Taqqu (1994) or Ortobelli et al. (2004). We assume $\lambda = 0.97$ according to Lamantia et al. (2004)

Distribution	Parameters	Estimators
Distributions with additivity property		
Normal one-step	$\mathcal{N}(\mu,\sigma)$	$\mu = 0.00021;\ \sigma = 0.01567$ $Q^{\text{theo}}_{0.01,1} = -0.0362$
Normal ten-step	$\mathcal{N}(\mu' = 10\cdot\mu, \sigma' = \sqrt{10}\sigma)$	$\mu' = 0.00211;\ \sigma' = 0.04954$ $Q^{\text{theo}}_{0.01,10} = -0.1132$
Stable one-step	$S(\alpha,\beta,\delta,\mu)$	$\alpha = 1.65725; \beta = -0.18135; \delta = 0.00881; \mu = -0.00007$ $Q^{\text{theo}}_{0.01,1} = -0.0535$
Stable ten-step	$S(\alpha,\beta,\delta' = 10^{1/\alpha}\cdot\delta, \mu' = 10\cdot\mu)$	$\alpha = 1.65725; \beta = -0.18135; \delta' = 0.03535; \mu' = -0.00068$ $Q^{\text{theo}}_{0.01,10} = -0.2150$
Distributions without additivity property		
Skewed student(t) one-step	$SkS(\mu,\sigma,\nu,\xi)$	$\mu = 0.00012;\ \sigma = 0.01659, \nu = 3.54679, \xi = 0.93552$ $Q^{\text{theo}}_{0.01,1} = -0.463$
Skewed student (t) ten-step	-	-
GED one-step	$GED(\mu,\sigma,\nu)$	$\mu = 0.00087, \sigma = 0.01563, \nu = 1.03591$ $Q^{\text{theo}}_{0.01,1} = -0.420$
GED ten-step	-	-

$Q^{\text{theo}}_{\alpha,\tau}$: α-quantile of the theoretical τ-step distribution

Table 2: Parameter estimation of the considered distributions for DAX 30 (08-20-1995 to 06-29-2007)

Model	w	$-\mathrm{Q}_{0.01}(1\|t)$	Area B	Area A	$-\mathrm{Q}_{0.01}(\mathbf{10} \mid t)$	Area B	Area A	rz	∅ multi.	∅ lrc
Normal time series										
Theoretical	X	0.0362			0.1132					
Hist. Vol.	250	0.0363	0.016	0.000	0.1133	0.110	0.019	0.006	3.05767	0.3258
	1000	0.0361	0.012	0.000	0.1133	0.091	0.017	0.004	3.05737	0.3262
EWMA	250	0.0363	0.003	0.000	0.1147	0.000	0.000	0.001	3.0959	0.3339
Hist. Sim.	250	0.0361	0.107	0.011	0.1130	0.127	0.025	0.003	3.0711	0.3267
	1000	0.0362	0.094	0.008	0.1132	0.097	0.009	0.006	3.0622	0.3257
St. Parameters	250	0.0408	0.000	0.000	0.1381	0.000	0.000	0.000	3.0119	0.3886
	1000	0.0382	0.000	0.000	0.1236	0.000	0.000	0.000	3.0225	0.3576
SEWMA	250	0.0387	0.000	0.000	0.1305	0.000	0.000	0.000	3.0287	0.3675
	1000	0.0374	0.000	0.000	0.1209	0.000	0.000	0.006	3.0469	0.3506
Stable time series										
Theoretical	X	0.0535			0.2150					
Hist. Vol.	250	0.0519	0.269	0.071	0.1648	0.712	0.576	0.082	3.1539	0.4790
	1000	0.0558	0.174	0.035	0.1774	0.591	0.449	0.047	3.0840	0.5002
EWMA	250	0.0463	0.512	0.210	0.1463	0.886	0.805	0.270	3.3541	0.4540
Hist. Sim.	250	0.0562	0.052	0.006	0.1908	0.468	0.318	0.005	3.0705	0.5278
	1000	0.0537	0.078	0.006	0.2354	0.248	0.155	0.010	3.0608	0.6398
St. Parameters	250	0.0540	0.064	0.008	0.2235	0.095	0.031	0.087	3.1197	0.6248
	1000	0.0537	0.075	0.017	0.2366	0.151	0.053	0.026	3.0721	0.6037
SEWMA	250	0.0478	0.348	0.042	0.1968	0.319	0.104	0.051	3.1619	0.5638
	1000	0.0483	0.295	0.044	0.1860	0.341	0.110	0.027	3.1308	0.5574

w: window length; $\mathrm{Q}_\alpha(\tau|t)$: α-quantile of the τ-step distribution; Area B/Area A: proportion of time series with rejected hypothesis $p \leq \mathrm{Q}_\alpha(\tau|t)$ to a significance level of $a = 0.1/a = 0.01$; rz: proportion of time series, where $h = 4$ is reached; ∅ multi.: average level of the multiplicator; ∅ lrc: average level of regulatory capital

Table 3: Results for the normal and stable time series
Quantile estimators, results for the critical areas, ratio of red zone estimators, average multiplication factor, and average level of regulatory capital for the time series with normal (upper part) and stable (bottom part) distributed random values

Model	w	$-Q_{0.01}(1\|t)$	Area B	Area A	rz	∅ multi.	∅ lrc
GED time series							
Theoretical	X	0.0463					
Hist. Vol.	250	0.0379	0.967	0.821	0.251	3.2930	0.3716
	1000	0.0380	0.953	0.798	0.254	3.2597	0.3690
EWMA	250	0.0371	0.998	0.951	0.482	3.3687	0.3810
Hist. Sim.	250	0.0469	0.080	0.011	0.002	3.0697	0.3738
	1000	0.0464	0.074	0.011	0.006	3.0608	0.3838
St. Parameters	250	0.0605	0.000	0.000	0.011	3.0313	0.6984
	1000	0.0602	0.000	0.000	0.001	3.0068	0.6843
SEWMA	250	0.0462	0.05	0.003	0.029	3.0899	0.5596
	1000	0.0469	0.022	0.001	0.006	3.0628	0.5579
Skewed student-t time series							
Theoretical	X	0.0420					
Hist. Vol.	250	0.0354	1.000	0.966	0.264	3.3000	0.3251
	1000	0.0355	1.000	0.968	0.281	3.2840	0.3237
EWMA	250	0.0358	1.000	0.935	0.313	3.3687	0.3521
Hist. Sim.	250	0.0420	0.094	0.017	0.006	3.0706	0.3089
	1000	0.0420	0.098	0.010	0.010	3.060	0.3091
St. Parameters	250	0.0672	0.000	0.000	0.000	3.0021	0.8046
	1000	0.0680	0.000	0.000	0.000	3.0001	0.8226
SEWMA	250	0.0489	0.000	0.000	0.000	3.0081	0.6386
	1000	0.0498	0.000	0.000	0.000	3.0047	0.6269

w: window length; $Q_\alpha(\tau|t)$: α-quantile of the τ-step distribution; Area B/Area A: proportion of time series with rejected hypothesis $p \leq Q_\alpha(\tau|t)$ to a significance level of $a = 0.1/a = 0.01$; rz: proportion of time series, where $h = 4$ is reached; ∅ multi.: average level of the multiplicator; ∅ lrc: average level of regulatory capital

Table 4: Results for the GED and skewed student-t time series

Quantile estimators, results for the critical areas, ratio of red zone estimators, average multiplication factor, and average level of regulatory capital for the time series with skewed student-t (upper part) and GED (bottom part) distributed random values

Does Basel II destabilize financial markets? An agent-based financial market perspective

Oliver Hermsen*

Abstract
We use a financial market model that is able to replicate stylized facts of financial markets quite successfully. We adjust this model by integrating regulations of Basel II concerning market risk. The result is a considerable destabilization of the regulated financial market with a significant increase of extreme events (extraordinary profits and losses). Since the intention of Basel II regulations is to ensure banks have enough regulatory capital to withstand periods involving extraordinary losses, it is alarming that - on the contrary - these regulations may provoke an increase in precisely such extraordinary events.

Keywords:
Heterogeneous agent models, Basel II, bank regulation, financial markets, market risk

JEL-Classification:
G15, G18, G32

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1 Introduction

In this paper we use a financial market model with heterogeneous interacting agents to show that the regulations of Basel II may lead to a destabilization of financial markets. This is obviously the direct opposite of what the regulatory authority aims to achieve.

In the last two decades, many current topics on economics and finance were illuminated with behavioral, agent-based approaches such as heterogeneous agent models (HAMs) (Hommes, 2006; LeBaron, 2006).[1] For instance, economic phenomena such as the effects of Tobin taxes, central bank interventions, or price limiters on financial markets were explored with HAMs (Mannaro et al., 2008; Westerhoff & Dieci, 2006; He & Westerhoff, 2005; Westerhoff, 2003). In this paper, a novel field of broad public interest is explored using an interacting agent-based approach - the Basel II regulations for market risk and their consequences for financial markets.

The Basel II framework was implemented to ascertain whether financial institutions had sufficient capitalization. The framework intends to ensure, for instance, that banks are able to withstand periods involving extraordinary losses in financial markets (Crouhy et al., 2006).

The "International Convergence of Capital Measurement and Capital Standards" (Basel II) allows the capital requirements for market risk to be calculated by means of a Value-at-Risk (VaR) model when performing the Internal Models Approach. Here, the Basel Committee for Banking and Supervision (BCBS) does not stipulate that banks use a special type of model, but provides a special formula to determine the level of regulatory

[1] For interesting contributions see, for instance, Kirman (1991), Bornholdt (2001), Brock and Hommes (1998), Chen & Yeh (2002), Farmer & Joshi (2002), de Grauwe & Grimaldi (2005), LeBaron et al. (1999) and Raberto et al. (2003).

capital. On trading days with sharp price decreases, the loss might be higher than the VaR, and a so-called ”backtesting exception” occurs. The formula considers the VaR and a multiplication factor that is raised if many backtesting exceptions occur in a quarter. Hence, the level of regulatory capital (lrc) increases notably on days with backtesting exceptions, especially if numerous consecutive backtesting exceptions lead to an increase of the multiplication factor (BCBS, 2006; Kerkhof & Melenberg, 2004).

In view of this situation, banks have two possibilities. On the one hand, they can raise their level of regulatory capital, although this is quite an expensive option for banks. On the other hand, they can sell risky assets from their portfolio to lower the risk (Benink et al., 2008).

In this paper, we explore the consequences of what happens when banks choose the selling option. Benink et al. (2008) argue that the Basel II regulations lead to a harmonization of bank behavior to maintain a special level of regulatory capital. As a result of the regulations, banks use quite similar trading rules and - therefore - want to sell the same assets at the same time. We wish to explore and, to a certain extent, quantify the consequences of this bank behavior governed by Basel II regulations on a financial market in our HAM.

In this respect, we are faced with at least two problems. First, we do not know the exact number of institutional traders in the market. Consequently, we do not know the exact number of market participants who are expected to sell assets. The second problem is that the Basel II framework has only been implemented in national legislation by many countries for either a short time or not at all. There is therefore a lack of empirical data to explore this question. We perform a numerical analysis to shed light on this topic. As it turns out, we find that the ”selling option” may lead to a destabilization of financial markets.

The remainder of this paper is organized as follows. In the next section, the starting point of the numerical analysis, we describe Lux and Marchesi's (1999, 2000) heterogeneous agent model. This model is able to mimic the stylized facts of financial markets quite successfully. Subsequently, we adjust this model by integrating regulation aspects of Basel II. In this way, we are able to compare the behavior of financial markets with and without the regulations determined by the BCBS. In this analysis, we vary the ratios of institutional investors concerned by the Basel II regulations. In section 3, the procedure concerning the numerical analysis is introduced. Measuring the destabilization of financial markets by the volatility, Hill tail index and distortion, the results of section 4 provide strong evidence that destabilization may increase when the regulations of Basel II are adopted. The last section offers a number of conclusions.

2 The model

2.1 Lux and Marchesi's basic model

The basic model used in our numerical analysis is that of Lux and Marchesi (1999, 2000). This model was inspired by the work of Weidlich and Haag (1983) and Kirman (1991), and later extended by Alfarano et al. (2005) and Alfarano and Lux (2007), among others. Interacting agents generate a dynamic model that is able to mimic the stylized facts of financial markets remarkably well. The following equations constitute the model[2]. There are two types of agents: chartists and fundamentalists. Chartists (c) can switch between optimistic ($+$) and pessimistic ($-$) moods, based on the current price trend and the mind-

[2]Only a brief outline of the model is given. For a detailed description, cp. Lux & Marchesi (2000)

set of the majority. The opinion index x

$$x = \frac{n_+ - n_-}{n_c}, x \in [-1, 1] \tag{1}$$

defines whether optimistic ($x > 0$) or pessimistic ($x < 0$) chartists hold the majority where n_+ and n_- are the the number of agents in the respective group and n_c is the total number of chartists. Transitions rates between these two groups within a small time period Δt are given by $\pi_{+-}\Delta t$ and $\pi_{-+}\Delta t$ as

$$\begin{array}{rcl} \pi_{+-} & = & \nu_1 \left(\frac{n_c}{N} \exp(U_1)\right) \\ \pi_{-+} & = & \nu_1 \left(\frac{n_c}{N} \exp(-U_1)\right) \end{array}, \; U_1 = \alpha_1 x + \alpha_2 \frac{\dot{p}_t}{\nu_1}. \tag{2}$$

Here, ν_1 marks the frequency of opinion revaluation, α_1 and α_2 describe the importance attached by agents to the price trend and majority opinion, respectively, p_t determines the market price at time t, and N is the number of all agents. π_{+-} determines the transition rate of switching from the group of pessimistic chartists to the group of optimistic chartists and π_{-+} determines the rate of transition in the opposite direction.

Individuals are not only able to switch between the groups of pessimistic and optimistic chartists. Depending on the expected gains, agents can also switch between chartists' and fundamentalists' strategies. In so doing,

$$z = \frac{n_c}{N}, z \in [1, 0] \tag{3}$$

describes the proportion of chartists. Transition rates for changes between the (sub-) group/s of chartists and fundamentalists are obtained with

$$\begin{array}{rcl} \pi_{+f} & = & \nu_2 \left(\frac{n_+}{N} \exp(U_{2,1})\right) \\ \pi_{f+} & = & \nu_2 \left(\frac{n_f}{N} \exp(-U_{2,1})\right) \end{array}, \; U_{2,1} = \alpha_3 \left(\frac{r + \frac{\dot{p}_t}{\nu_2}}{p_t} - R - s \left| \frac{p_t^f - p_t}{p_t} \right| \right)$$
$$\begin{array}{rcl} \pi_{-f} & = & \nu_2 \left(\frac{n_-}{N} \exp(U_{2,2})\right) \\ \pi_{f-} & = & \nu_2 \left(\frac{n_f}{N} \exp(-U_{2,2})\right) \end{array}, \; U_{2,2} = \alpha_3 \left(-\frac{r + \frac{\dot{p}_t}{\nu_2}}{p_t} + R - s \left| \frac{p_t^f - p_t}{p_t} \right| \right), \tag{4}$$

where ν_2 is the frequency of transition, α_3 is the pressure exerted by profit differentials, s is a discount factor for the expected profits, R are the average real returns from other investments, r is the nominal dividend of the asset, and p_t^f describes the fundamental value of the asset at time t. The associated transition rates can be interpreted in the same way as in formula (2): within a small time period Δt a change from state b to a is given by $\pi_{ab}\Delta t$.

The third decisive factor for the dynamics of the model is the price formation process. Here, positive [resp., negative] excess demand drives the market price upwards [resp., downwards] by a fixed amount. Following Hommes' (2006) notation, the rates of a price change occurring within Δt are determined by:

$$\begin{aligned} \pi_{\uparrow p} &= \min[\max[0, \beta(ED + \mu)], 1] \\ \pi_{\downarrow p} &= \min[-\min[0, \beta(ED + \mu)], 1], \end{aligned} \tag{5}$$

where β is a parameter for the reaction speed of the market-maker that realizes the price adjustment and μ is a noise term. $\pi_{\uparrow p}$ and $\pi_{\downarrow p}$ are the transition rates for an increase or decrease of the market price. ED is the excess demand determined by the different groups of the model as described in section 2.3 below in more detail.

In short, the change in the proportion of pessimistic and optimistic chartists $\dot{x}$, the change in the proportion of chartists $\dot{z}$, and the change in market price $\dot{p}_t$ over time are the driving forces for the dynamics of the model.

This model is the starting point for our further analysis. We would like to explore how regulations of the BCBS can affect a financial market, as characterized by this model.

2.2 The Basel II regulations for market risk

Let us now take a closer look at the Basel II regulations concerning market risk. Here, the BCBS focuses on the cumulative loss distribution of ten trading days. Over a period of at least 250 trading days (one year) the cumulative loss distribution of a portfolio has to be estimated by the financial institute. For the determination of the loss distribution, losses are considered as positive and profits as negative values. The level of regulatory capital is based on the risk measure Value-at-Risk (VaR).

From a statistical point of view, the VaR is defined as the $1 - \alpha$ quantile of the loss distribution, where α is a level of significance: 1% for instance. In an economic sense, the VaR is defined as a threshold or severe loss that is not exceeded at $\alpha * 100\%$ of trading days (Marrison, 2002; McNeil et al., 2005).

However, the loss distribution for ten cumulative losses is difficult to estimate. When the VaR concerns the loss of investments, the VaR may be obtained from the corresponding quantile of the distribution of the returns. This method to calculate VaR is employed in the numerical analysis of section 3.

According to Reiss and Thomas (2007), we can define the τ-step VaR at time t, $\mathrm{VaR}_\alpha(\boldsymbol{\tau}|t)$, given the portfolio value at time t with V_t and the quantile of the (cumulative) τ-step return distribution at time t with $Q_\alpha(\boldsymbol{\tau}|t)$ with[3]

$$\mathrm{VaR}_{1-\alpha}(\boldsymbol{\tau}|t) = V_t \left(1 - \exp\left((Q_\alpha(\boldsymbol{\tau}|t)\right)\right). \tag{6}$$

Since we carry out a univariate analysis, we use $V_t = p_t$. To calculate the VaR there exist several approaches. The most traditional and employed methods for this calculation are presented in the Appendix.

The next important aspect is to determine a special VaR model. Since the BCBS

[3] The bold $\boldsymbol{\tau}$ in the formula symbolizes the return distribution for the time period from t to τ days.

does not prescribe a special model to determine this risk measure, not every bank uses the same method. VaR models differ mainly with regard to how they characterize the distribution of the return distribution and how they model volatility. However, it is well known that institutes mainly use practical VaR methods with simple assumptions rather than GARCH or related methods proposed by various researchers over the last decade (Marrison, 2002). Due to this fact, we assume that banks carry out three quite simple VaR methods - historical volatility, historical simulation, and the EWMA model, which are described in the appendix. We assume that a third of financial institutes use historical volatility, the middle third uses historical simulation and the last third uses the EWMA model. [4]

After having defined the VaR, we can present the following formula to determine the regulatory capital for market risk prescribed by the BCBS (2006, 718 (LXXVI) (i)):

$$\mathrm{lrc}_{1|t} = \max\left(\frac{h}{60}\sum_{i=1}^{60}\mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t)\right), \tag{7}$$

where $\mathrm{VaR}_{0.99}(\mathbf{10}|t-i)$ is the 99%-VaR of the (cumulative) loss distribution of the next 10 periods (days), $\mathrm{lrc}_{1|t}$ is the level of regulatory capital in the next period, and h is a multiplier. The multiplier ranges between $h = 3$ and $h = 4$ (Chebyshev's inequality is the justification for this range, as described in Stahl (1997) or Danielsson et al. (1998)). It is a requirement of the bank and supervisory authority to evaluate whether a VaR model is suitable for capturing risk. For this, a backtesting procedure based on $\mathrm{VaR}_{0.99}(1|t)$ has to be performed. Based on the number of backtesting exceptions, factor h is raised. A backtesting exception occurs when loss is higher than the VaR in one day. If the multiplier reaches a level of $h = 4$, the supervisory authority can force the bank to change its VaR

[4] However, the results remain quite stable if we assume other combinations of VaR models. An analysis for the extreme assumption that all financial institutes use the same model clarified this aspect.

approach. In the Basel II framework, the model is categorized in the green zone for $h = 3$, in the yellow zone for $3 < h < 4$, and in the red zone for $h = 4$.

Furthermore, a backtesting exception affects not only h but also $\text{VaR}_{0.99}(\mathbf{10}|t-i)$. Hence, both decisive terms in the calculation of the level of regulatory capital are increased when a backtesting exception occurs. How will a bank react to such an incident?

From the point of profit maximization, a bank might strive to keep regulatory capital low. In contrast to acquiring loan capital, it is much more expensive for a bank to acquire regulatory capital. Consequently, instead of raising the level of regulatory capital, a bank might sell risky assets in case of a backtesting exception to maintain regulatory capital at a moderate level (Benink et al., 2008).

In the next subsection, Lux and Marchesi's model will be adjusted to explore the effect of these regulations on financial markets.

2.3 The adjusted model

Our previous considerations are incorporated in the model by introducing a new group of agents that sells assets on trading days with backtesting exceptions, called "regulated traders". Agents of this group are institutional investors, since Basel II regulations are only obligatory for them. This does not mean that the group's market participants renounce their beliefs in the trading rules they previously used. They are more or less forced by the regulator to behave against their convictions. Benink et al. (2008) allude here to a "harmonization" of behavior in this context.

Since Lux and Marchesi's model is defined in continuous time, it is also important whether the VaR is exceeded at the beginning or the end of a day. The calculation of the level of regulatory capital is based on the closing price. Therefore, we define $p_{VaR} =$

$p_{t-1} - \text{VaR}_{0.99}(1|t)$ at integer time steps as the price when an investor suffered a loss amounting to the VaR. Hereby, p_{t-1} is the price at the end of the last trading day.[5]

If the market price falls below the VaR ($p_{VaR} > p_t$) at the beginning of the day, traders may hope to see a price recovery in the course of the trading day so that no backtesting exception occurs at the end of the day. In the event of a price recovery above the VaR level ($p_{VaR} < p_t$), regulated traders will revert to the trading rules in which they believe, and no traders from the chartist and fundamentalist groups will switch to the group of regulated traders. The shorter the remaining trading hours are, the higher the probability that institutional investors will be forced to become regulated and sell risky assets to prevent a sharp increase in the level of regulatory capital.

The question now is how many institutional investors there are in the market and how many of them behave in the described manner. This question is impossible to answer convincingly. For this reason, in the numerical analysis, we vary the proportion of institutional investors N_{inst} in the market. In this way, we are able to explore the consequences if only a small or a larger proportion of the market is regulated by bank supervision.

Due to these preliminary considerations, we add or adjust the following equations. Only if a backtesting exception occurs ($p_{\text{VaR}} \geq p_t$), institutional chartist/fundamentalist traders switch from their groups to the group of regulated traders, symbolized by r, within a small time period Δt by π_{rf}, π_{r+} and π_{r-}. If there is no backtesting exception ($p_{\text{VaR}} < p_t$), of course, no agent will switch to the group of regulated traders. After a price recovery above p_{VaR} ($p_{\text{VaR}} < p_t$ and $p_{\text{VaR}} > p_{t-\Delta t}$) they surely switch back to the trading

[5] Remember that a backtesting exception according to Basel II only occurs when a loss is larger than the VaR at the end of a trading day. An exceedance of the VaR between two integer time steps is only an indication that a backtesting exception may occur.

rules in which they believe according to π_{fr}, π_{+r} and π_{-r}. We obtain

$$
\begin{aligned}
\pi_{rf} &= \pi_{r+} &= \pi_{r-} &= d, \text{ if } p_{\text{VaR}} \geq p_t \qquad d \in [0,1] \\
\pi_{rf} &= \pi_{r+} &= \pi_{r-} &= 0, \text{ if } p_{\text{VaR}} < p_t \\
\pi_{fr} &= \pi_{+r} &= \pi_{-r} &= 1, \text{ if } p_{\text{VaR}} < p_t \quad \text{and } p_{\text{VaR}} > p_{t-\Delta t},
\end{aligned}
\tag{8}
$$

where d is the elapsed time from the beginning of a trading day. Here, p_{VaR} is defined at integer time steps as $p_{\text{VaR}} = p_{t-1} - \text{VaR}_{0.99}(1|t)$. If price p_t is equal to or smaller than p_{VaR}, the loss associated with $\text{VaR}_{0.99}(1|t)$ is realized. $p_{t-\Delta t}$ symbolizes the price a small time increment ago. When a backtesting exception diminishes in the course of a trading day all traders switch back to their respective group. Since they are dependent on the conviction of traders, the opinion index x and the proportion of chartists z do not change.

With the introduction of the regulated traders, we have to adjust the excess demand function. The reason for this is that regulated traders have to (completely) apply other trading rules to those of the other groups. In the following, we describe the parts of the excess demand and especially emphasize the changes compared to Lux and Marchesi's (1999/2000) basic model for each of the groups of fundamentalists, chartists and regulated traders.

2.3.1 The fundamentalists' excess demand

We have to adjust excess demand ED_f from Lux and Marchesi's (1999, 2000) model for fundamentalists. In this model, the proportion of fundamentalists' traders $1 - z$ orders assets when price p_t is below the fundamental price p_t^f and sells assets when the price exceeds the fundamental value. The amount of orders is expressed by T_f. This leads to

$$ED_f = (1 - z)\ T_f\ (p_t^f - p_t). \tag{9}$$

When considering the regulated traders to explore the consequences of the Basel II regulations, equation (9) has to be adjusted. When the price is below the VaR ($p_t < p_{\text{VaR}}$), the expected gains will usually be high for fundamentalists, since the market price is usually below the fundamental price on trading days with backtesting exceptions. This means that fundamentalists usually want to buy assets when such a backtesting exception occurs. However, in order to obtain an adequate level of regulation capital, fundamentalist traders are forced to sell risky assets in such a situation if the Basel II regulations apply to them. They have to switch to the group of regulated traders $v = N_r/N$, where N_r is the total number of traders governed by Basel II regulations. As a part of this group, the proportion of fundamentalists that have to switch groups is denoted v_f. Depending on the occurrence of a backtesting exception, fundamentalists' excess demand can be formalized as follows in the adjusted model:

$$
\begin{aligned}
ED_f &= (1-z)\, T_f\, (p_t^f - p_t) \qquad , \text{ if } p_{\text{VaR}} < p_t. \\
ED_f &= (1-z-v_f)\, T_f\, (p_t^f - p_t), \text{ if } p_{\text{VaR}} \geq p_t.
\end{aligned}
\tag{10}
$$

At time steps with backtesting exceptions, the proportion of regulated fundamentalists v_f has to follow the rules of the regulation authority. This fraction is therefore subtracted from the total number of traders together with the proportion of chartists z, so that the proportion shrinks to $(1 - z - v_f)$. All other elements of the fundamentalists' excess demand remain constant, as described in (9). The consequences for the chartists' excess demand are explored in the next subsection.

2.3.2 Chartists' excess demand

In Lux and Marchesi's (1999, 2000) model we find two groups of chartists – optimistic and pessimistic ones. Chartists chase price trends and – depending on the price development

– we have either more pessimistic (opinion index x is negative) or optimistic (opinion index x is positive) chartists. Hence, the excess demand consisting of the opinion index x, the proportion of chartists z and the number of orders placed by the chartists T_c is

$$ED_c \quad = x\, z\, T_c, \text{ if } p_{\text{VaR}} < p_t. \tag{11}$$

When we define the excess demand for the model with regulated traders, we should bear in mind the behavior of the two different chartist groups. For optimistic chartists, the same holds true as for the fundamentalists' group. They want to buy assets and are forced by the regulation authority to do the opposite at time steps with backtesting exceptions if $p_t < p_{\text{VaR}}$. Hence, we have to subtract the group of regulated optimistic chartists v_+ from the group of chartists z when adjusting their excess demand for time steps with backtesting exceptions:

$$ED_c \quad = x\,(z - v_+)\, T_c, \text{ if } p_{\text{VaR}} \geq p_t. \tag{12}$$

Since pessimistic chartists will sell risky assets in any case, they play a special role. If the pessimistic chartists who are affected by the regulations wish to sell more assets than they are forced to sell, they will sell them anyway. The excess demand generated by the regulated pessimistic chartists applying their usual chartists' rules is given as $ED_{-;c}$. Pessimistic chartists are only affected by the regulations if the regulated pessimistic chartists are forced to sell more assets than planned. The excess demand generated by the pessimistic chartists if forced to apply regulations is given as $ED_{-;r}$. We only have to subtract the group of regulated pessimistic chartists v_- in addition to v_+ if $\mid ED_{-;r} \mid > \mid ED_{-;c} \mid$. Together with (11) and (12), we then obtain the following case distinction for the chartists' excess demand:

$$\begin{aligned} ED_c &= x\,z\,T_c &&, \text{ if } p_{\text{VaR}} < p_t \\ ED_c &= x\,(z - v_+)\,T_c &&, \text{ if } p_{\text{VaR}} \geq p_t \text{ and } \mid ED_{-;c} \mid > \mid ED_{-;r} \mid . \\ ED_c &= x\,(z - v_+ - v_-)\,T_c, && \text{if } p_{\text{VaR}} \geq p_t \text{ and } \mid ED_{-;c} \mid \leq \mid ED_{-;r} \mid \end{aligned} \tag{13}$$

Finally, we take a closer look at the excess demand of the newly introduced group – the regulated traders.

2.3.3 The excess demand of regulated traders

The group of regulated traders consists of institutional investors from the groups of fundamentalists, as well as optimistic and pessimistic chartists who are affected by the regulations. However, the different groups are affected by backtesting exceptions in different ways, as described in the previous subsections.

Of course, when no backtesting exceptions occur, there is no need to apply regulations. We have

$$ED_r = 0 \text{ if } p_{\text{VaR}} < p_t. \tag{14}$$

We use a similar rule for excess demand of the regulated traders ED_r as for the fundamentalists' excess demand for time steps with backtesting exceptions. Here, we combine the amount of ED_r with the amount by which the VaR is extended. Hence, we obtain the plausible setting that the higher the VaR is extended, the greater the reaction of regulated traders. This is conceptually similar to modeling the fundamentalists' excess demand. For them, the gap between the market price and the fundamental price is decisive to excess demand. For regulated traders, the gap between the market price and the VaR is crucial. T_r is the number of units sold by regulated traders.

If only fundamentalists and optimistic chartists are governed by the regulations (v_f

and v_+), we obtain

$$ED_r \quad = (v_+ + v_f)\ T_r\ (p_t - p_{\text{VaR}}),\ \text{if}\ p_{\text{VaR}} \geq p_t\ \text{and}\ \mid ED_{-;c} \mid > \mid ED_{-;r} \mid . \tag{15}$$

Remember that this occurs if the excess demand of the regulated pessimistic chartists who apply chartists' trading rules is higher than the excess demand of the regulated pessimistic chartists who apply regulations.

If the opposite holds true, traders from all groups will be affected by the regulations. Therefore, it follows that

$$ED_r \quad = (v_f + v_+ + v_-)\ T_r\ (p_t - p_{\text{VaR}}),\ \text{if}\ p_{\text{VaR}} \geq p_t\ \text{and}\ \mid ED_{-;c} \mid \leq \mid ED_{-;r} \mid . \tag{16}$$

When we combine equations (14), (15) and (16), we obtain the following case distinction for the excess demand of regulated traders

$$\begin{aligned}
ED_r &= 0 &&,\ \text{if}\ p_{\text{VaR}} < p_t. \\
ED_r &= (v_+ + v_f)\ T_r\ (p_t - p_{\text{VaR}}) &&,\ \text{if}\ p_{\text{VaR}} \geq p_t\ \text{and}\ \mid ED_{-;c} \mid > \mid ED_{-;r} \mid . \\
ED_r &= (v_f + v_+ + v_-)\ T_r\ (p_t - p_{\text{VaR}}) &&,\ \text{if}\ p_{\text{VaR}} \geq p_t\ \text{and}\ \mid ED_{-;c} \mid \leq \mid ED_{-;r} \mid .
\end{aligned} \tag{17}$$

According to the excess demand of Lux and Marchesi's model, the total excess demand of the adjusted model is the excess demand of chartists and fundamentalists plus the excess demand of regulated traders:

$$ED = ED_c + ED_f + ED_r. \tag{18}$$

The remaining question is how market stability is measured.

2.4 Measuring market stability

With regard to measures for market stability, it is useful to focus on extraordinary events. As previously mentioned, the BCBS identifies extraordinary losses as being especially problematic for financial institutes, meaning that an increase in such losses is one of the main reasons why financial stability is compromised. In the following, we introduce three measures that give us an idea of the amount of extraordinary losses and the risk of them occurring[6].

Extraordinary losses mainly occur in relation to volatility clusters. If more volatility clusters occur, the average volatility usually increases. Hence, the average volatility is a useful measure of market stability. The smaller its value, the higher the stability of the financial market. We define volatility simply as the standard deviation of the returns:

$$V = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \overline{Y}\right)^2}. \tag{19}$$

The returns Y_t are defined as $Y_t = \ln p_t - \ln p_{t-1}$ at integer time steps. In the numerical analysis of chapter 4, we consider time series with $T = 7000$ observations.

However, BCBS' incentives in choosing the VaR as the relevant risk measure for internal models are to capture the extreme events and be prepared for their occurrence (McNeil et al., 2005). In this context, the Hill tail index is a crucial additional measure to report the incidence of these extreme events. To calculate the index, the returns of a sample are first arranged in descending order $Y_T > Y_{T-1} > \cdots > Y_{t-k} > \cdots > Y_1$. Here, k denotes the number of observations in the tail of the sample. The Hill tail index can be then estimated via

$$\alpha^H = \left(\frac{1}{k}\sum_{i=1}^{k}\left(\ln \mid Y_{T-i+1} \mid - \ln \mid Y_{T-k} \mid\right)\right)^{-1}. \tag{20}$$

According to Lux and Ausloos (2002), 2.5% and 5% are often used as tail fractions. Interpreting the tail index α^H, we can estimate the number of existing moments. For instance,

[6]These measures are also used in other surveys to describe financial market stability, such as in Westerhoff (2008).

an α^H below 2 indicates that no second moment (hence, no variance) exists. Thus, a Hill index below 3.5 indicates three existing moments. Therefore, the Hill index is quite appropriate here to measure the change in the number of extremal events as a consequence of the regulations. The lower the Hill index, the lower the stability of the financial market, since more extraordinary losses occur.

Additionally, we consider the distortion of the financial market. A short explanation is necessary with regard to its definition. Since we know the fundamental value for every time step, we can calculate the mean absolute deviation between the realized log price and the log fundamental price. Distortion D is therefore defined as:

$$D = \frac{1}{T} \sum_{t=1}^{T} \mid \ln p_t - \ln p_t^f \mid \tag{21}$$

with t at integer time steps. If the financial market is highly distorted, there is a higher risk of the emergence of bubbles and crashes. If the price greatly exceeds the fundamental value, there is a high risk that many agents will become fundamentalists. If this happens, the price reverts to the fundamental value quite rapidly increasing the risk of extraordinary losses. Distortion is therefore also quite a relevant measure of the stability of the financial market.

After introducing a model and measures of stability that are able to shed light on the consequences of the Basel II regulations for financial markets, we will now focus on how the numerical analysis is performed in the following section to obtain reliable results.

3 The numerical analysis

The procedure concerning the numerical analysis is the same as described in Lux and Marchesi (2000). The technical details of the simulation procedure are described in detail in their work[7]. However, for a better understanding of the results, it is necessary to describe how the small time period Δt of the transition rates is chosen in the numerical analysis. Although the dynamics of the model is continuous in time, we discretize time in the simulations. For this, it is important choosing Δt sufficient small to obtain reliable results. Lux and Marchesi (2000) carried out the following approach inspired by micro simulations in the area of mean field approximations.

They distinguish between normal times and high volatility times during volatility outbursts. In normal times the small time period Δt that is necessary to determine the transition rates in the simulation is set to 0.01. During volatility outbursts the simulations' precision is increased by a factor 5 by fixing Δt to 0.002. The consequence of this is a division of the rates given in formulae (2) and (4) by 100 or 500, respectively, in the numerical analysis. Then, we obtain the probability for a change of the trading rule within the time interval $[t, t + \Delta t]$ for any single agent. Consequently, there are 100 to 500 possibilities for any agent to switch to another (sub-)group depending on the precision of the simulation.[8]

[7]One additional aspect has to be considered in connection with the regulated traders. Lux and Marchesi (2000) identify two absorbing states: $z = 0$ and $z = 1$. They avoid these absorbing states in the numerical analysis by preventing agents from changing their strategy when less than four members remain in the respective groups. Furthermore, concerning the adjusted model we assume that these remaining members are not institutional investors, since they would be forced to change groups at the end of a trading day if a backtesting exception occurs. By doing so, a breakdown of the simulation in the absorbing states can be prevented.

[8]The further proceeding is the same like in Lux and Marchesi's simulations. The actual value of the transi-

Lux and Marchesi mention the lack of empirical observations concerning the parameters of their model. Since no empirical data is available yet, we use the same parameter setting as the two authors.[9] For a financial market without regulated traders, if $N_{inst} = 0$, we confirmed the results of Lux and Marchesi and received typical stylized facts of financial markets. Besides the appearance of volatility clusters, we observe leptokurtic or heavy-tailed return series. Furthermore, the returns appear symmetrical around zero, and the absolute and squared returns time series exhibit considerable serial correlation, whereas the time series of the returns show only little correlation.

In the next section, we will present our results for varying proportions of institutional investors of 10%, 20%, 30%, 40% and 50% (thus, $N_{inst} = 50,\ 100,\ 150,\ 200,$ and 250). Regarding T_r, we assume $T_r = T_f$. This is a conservative assumption for the orders placed in the market by regulated traders. For the parameter sets I - IV proposed by Lux and Marchesi, chartists place at least as many orders as fundamentalists. If we raise T_r to the level T_c of chartists, the (negative) excess demand of the regulated traders is even stronger on days with backtesting exceptions. Hence, even more assets would be sold by the regulated traders. This causes an even higher price decay.

In the following, we test how the artificial financial market (thus, how the stylized facts and three market stability parameters) reacts to Basel II regulations for the different situations.

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tion rate is compared with a random number obtained from a uniform distribution on [0,1]. If the random number is smaller than the transition rate, the transition into the respective group occurs. If it is greater, no change occurs.

[9]Lux and Marchesi confirm the results of their model for four different parameter sets. Here we use set II. Its results are assessed as very realistic by Lux/Marchesi (2000): $\nu_1 = 4$, $\nu_2 = 1$, $\beta = 4$, $T_c = 7.5$, $T_f = 5$, $\alpha_1 = 0.9$, $\alpha_2 = 0.25$, $\alpha_3 = 1$, $p_t^f = 10$, $r = 0.004$, $R = 0.0004$, and $s = 0.75$. We obtain very similar results for the other three sets, as for the chosen set II.

4 Results

We first analyze the results for one selective time series. We juxtapose the results for volatility, distortion, and the Hill index (with a tail sample of 5%). The results are presented in Figure 1. The left panels show the dynamics for the financial market without regulations. In the middle panels, 10% of traders are institutional investors who have to follow regulations. In the right panels this proportion increases to 40%.

Figure 1 comes about here

Comparing the return time series, we observe a profound increase of destabilization concerning volatility, as Table 1 shows. In the return time series of the financial market with a 10% proportion of institutional investors (mid upper panel of Figure 1), we identify more pronounced and more frequently emerging volatility clusters than in the basic situation, where no Basel II regulations are integrated in the model (left upper panel). However, severe profits and losses of approximately over 8% do not occur very frequently. This aspect changes significantly for the financial market with a proportion of 40% institutional investors (right upper panel of Figure 1). Here, very high profits and losses up to 12% can be realized much more frequently with unaltered significant volatility clusters.

Table 1 comes about here

The middle panels of Figure 1 present a considerable increase in extreme events. Comparing the histograms' tails of the return series, we can identify more returns larger than 6% for a proportion of 10% institutional investors (mid bottom panels) and - of course - also for a proportion of 40% institutional investors. Table 1 underlines these results with considerably decreasing values for the Hill tail index. With regard to distortion, we are unable to identify significant differences between the regulated time series and the basic model.

The BCBS chose the VaR as a risk measure to determine the level of regulatory capital to ascertain whether banks are prepared for extreme events. Paradoxically, the extreme events were able to increase due to the BCBS's own regulations.

Before exploring the results for the market stability parameters more generally, we would like to analyze the newly introduced group of regulated traders in further detail. Figure 2 aims to shed light on this topic.

Again, the upper panels present the return time series - the left represents a proportion of 10% institutional investors whereas the right shows the situation for a proportion of 40%. The three panels below present the proportion of agents that had to explore the regulations during one trading day or - in other words - the proportion of agents that use regulations against their convictions during one trading day. Remember that - dependent on the volatility - there are 100 to 500 time steps on each trading days considered in the numerical analysis. At each time step there are 500 agents using either chartists' (optimistic or pessimistic) or fundamentalists' strategies (cp. section 3). If a backtesting exception occurs, some of the institutional traders have to apply the regulations determined by the BCBS. The mid upper panel presents the proportion of regulated traders that believe in optimistic chartists' trading rules (inst_+). The other two panels are interpreted in the same way as the mid-upper panels for a proportion of regulated traders that believe in pessimistic chartists' trading rules (inst_-; mid-bottom panel), and fundamentalists' trading rules (inst_f; bottom panel), respectively.[10]

Figure 2 comes about here

[10] Remember that only at the end of the day all institutional investors apply regulations. Therefore, the proportion never sums up to the number of institutional investors in the market

At time steps with significant volatility clusters, this proportion increases with regard to both quantity and maximum value, especially for the groups of chartists. We conclude that backtesting exceptions occur more frequently in these time periods. As the chartists' proportions are higher during the volatility clusters (cp. Lux & Marchesi (2000)), it is obvious that their proportion will increase more significantly here compared to the fundamentalist proportion. In the fundamentalist group, on the other hand, we recognize an increase in frequency of backtesting exceptions rather than in maximum values connected with volatility clusters. However, we can also say that the proportion of regulated traders and, consequently, the number of agents applying regulation rules is quite low on average. This rate rarely increases above 2% for the chartist groups (for a proportion of 10% and 40% institutional investors) and 10% for the fundamentalist group (for 40% institutional investors).

Note, that a change in the group of regulated traders does not necessarily mean a higher number of orders or absolute excess demand placed in the market. The panels merely presents the proportion of chartists and fundamentalists who are forced to apply other trading rules. The number of orders can even decrease when applying this rule if a regulated trader sells few assets as a regulated trader (represented by a slightly negative excess demand) instead of buying many assets as a fundamentalist (represented by a highly positive excess demand).

However, it becomes apparent that, on average, especially for 10% institutional investors (left panels of Figure 2) low proportions of traders forced to apply regulations as "trading rules" cause the significant destabilization of the financial market described above (cp. Figure 1).

The results analyzed at the beginning of this section (cp. Figure 2) for the market stability parameters are confirmed in a broader simulation study with 200 time series. Indeed, as the upper panel of Figure 3 emphasizes, a significant increase in volatility can be observed. The boxplots visualize the results for varying proportions of institutional investors governed by regulations (from top to bottom 50%, 40%, 30% 20%, and 10%). We identify that the average volatility (black disk of the boxplots of Figure 3) increases constantly over 10% with increasing proportions of institutional investors. The boxplots visualize how the average volatility of each of the 200 time series is distributed. Not only the mean but also the median and quantiles increase considerably with increasing proportions of institutional investors. However, we can also identify larger variations from the mean - probably due to the clustered volatility. There are more severe outliers on the right-hand side than on the left-hand side of the boxplots. This can be interpreted by the fact that unanticipated risky times (represented by the $T = 7000$ days of each time series) with an average volatility of up to 1.6% seem to be more likely to occur than calm times with volatility below 1.0%.

The results concerning the Hill index in the middle panel of Figure 4 are quite significant. For this measure, we identify a constant and considerable decrease with increasing proportions of institutional investors. The median and quantiles of the boxplots also decrease relatively constantly, albeit, as with volatility, often with larger variations from the mean. This decrease can be interpreted as a severe increase in extraordinary profits and losses in the market, which - as already mentioned above - is contrary to the intention of the BCBS when it issued the regulations. By contrast, for the results concerning distortion (bottom panel), we are unable to identify a clear increase or decrease. The positions of the mean, median and quantiles are relatively constant.

Figure 3 comes about here

5 Conclusions

We have analyzed the impacts of Basel II regulations concerning market risk. For this purpose, we integrated crucial regulations into a model with interacting agents that are able to replicate stylized facts of financial markets very realistically.

The main result of the numerical analysis is a destabilization of the artificial financial market if some agents have to follow regulations. We can interpret this as follows: if banks wish to keep regulatory capital low and sell assets to reach this target, the financial market may be destabilized compared to a situation in which regulations are applied. Even for small proportions of traders who are affected by the regulations, this result is highly significant. Since the Basel II regulations intend to ascertain whether banks have sufficient regulatory capital to withstand periods involving extraordinary losses, it is alarming that - on the contrary - these regulations may cause an increase in precisely these extraordinary events.

Regarding the account for new regulation rules in view of the present financial market crises, it may be a good idea to force banks to maintain higher financial security in calm times with low volatility. Although the VaR is lower and less backtesting exceptions occur in calm times, it is important for financial institutes to get prepared for more turbulent times by means of a higher lrc. In combination with a relaxation of regulations concerning regulatory capital in turbulent times, this may lead to a stabilization of financial markets. It could be an interesting challenge for further research to explore the consequences of regulations in more detail - especially in times with sharp price decreases - in order to find adequate regulations to achieve greater market stability.

Appendix: Value-at-Risk approaches

In the numerical analysis, we use three VaR approaches commonly used in practice[11] (Holton, 2003). The formal description can be found in Table 2, together with a number of references.

Table 2 comes about here.

The first approach – the historical volatility approach – works with quite simple underlying assumptions of a normal distribution for the returns and equally weighted historical observations for the returns. This approach was proposed indirectly by the BCBS (2006, 718 (LXXVI) (c) and (f)). The reason for the simple distributional assumption is substantiated by the use of the ten-step loss distribution to calculate the level of regulatory capital (cp. formula (7)). Here, the normal distribution fulfills the additivity property. It is therefore applied, although it is unrealistic to assume the normal distribution for return distributions (Daníelsson et al. (1998)). Due to its importance, the τ-step quantile estimator is also depicted in Table 2.

The second approach, the exponential weighted moving average model (EWMA), also assumes a normal distribution for the returns of the historical time series. However, contrary to historical volatility, it weights recent returns higher by a decay factor λ. Thus, it is possible to capture the typical volatility clusters for financial time series.

The historical simulation focuses on the distributional assumption to predict the VaR more realistically than the historical volatility. It uses the empirical distribution of

[11] A survey study conducted among German banks clarified that these VaR are mainly applied in practice (Homburg & Scherpereel (2005))

the historically observed returns and predicts the ten-step return distribution by means of a bootstrap procedure. However, these historical observations are equally weighted as for historical volatility.

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Market Stability Parameters	0% inst. investors	10%	20%	30%	40%	50%
Volatility	0.01139	0.01271	0.01206	0.01326	0.01331	0.01392
Distortion	0.00824	0.00932	0.00842	0.00922	0.00920	0.00914
Hill Index	4.36776	4.05135	3.55399	3.31062	2.97629	2.55314

Table 1: Estimates for the selected time series

VaR Approach	Model Description	Residual Distribution	Quantile Estimation	Literature
Normal approaches				
Historical Volatility	$y_i = \mu + u_i$	$u_i = \sigma \epsilon_i$ $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$	$Q_\alpha(\boldsymbol{\tau}\|t) = \tau\widehat{\mu} + z_\alpha \sqrt{\tau}\widehat{\sigma}$	BCBS (2006, 718 (LXXVI) (c) and (f)) Danielsson et al. (1998)
EWMA	$y_i = \mu + u_i$	$u_i = \sigma_i \epsilon_i;$ $h_{t+1} = (1-\lambda)u_t^2 + \lambda h_t$ $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1);\ \lambda = 0.94$	$Q_\alpha(\boldsymbol{\tau}\|t) = z_\alpha \sqrt{\tau \widehat{h}_{1\|t}}$	Zangari (1996) Holton (2003)
Simulation approach				
Historical Simulation	One-step: $\{y_i\}_{i=1}^n$ τ-step: $\widetilde{y}_{j,t+\tau} = \sum_{k=1}^{\tau} \widetilde{y}_{j,t+k}$, with τ series of $\{\widetilde{y}_i\}_{i=1}^n$ $j = 1, \ldots, 5000$	Empirical	One-step: $Q_\alpha(1\|t) = \widehat{q}_\alpha(\{y_i\})$ τ-step: $Q_\alpha(\tau\|t) = \widehat{q}_\alpha(\{\widetilde{y}_i\})$	McNeil et al. (2004)

z_α: α-quantile of the normal distribution; $Q_\alpha(\boldsymbol{\tau}|t)$: α-quantile of the τ-step return distribution; $\{y_i\}_{i=1}^n$: series of returns; $\{\widetilde{y}_i\}_{i=1}^n$: series of randomized one-step returns; $\widehat{q}_\alpha(\{\widetilde{y}_i\})$ and $\widehat{q}_\alpha(\{y_i\})$: quantiles of the respective series; h_{t+1}: forecast for $t+1$ of the conditional variance. For the quantile estimator of the EWMA approach, we assume the usual simplification $\mu = 0$.

Table 1: Survey of Value-at-Risk approaches

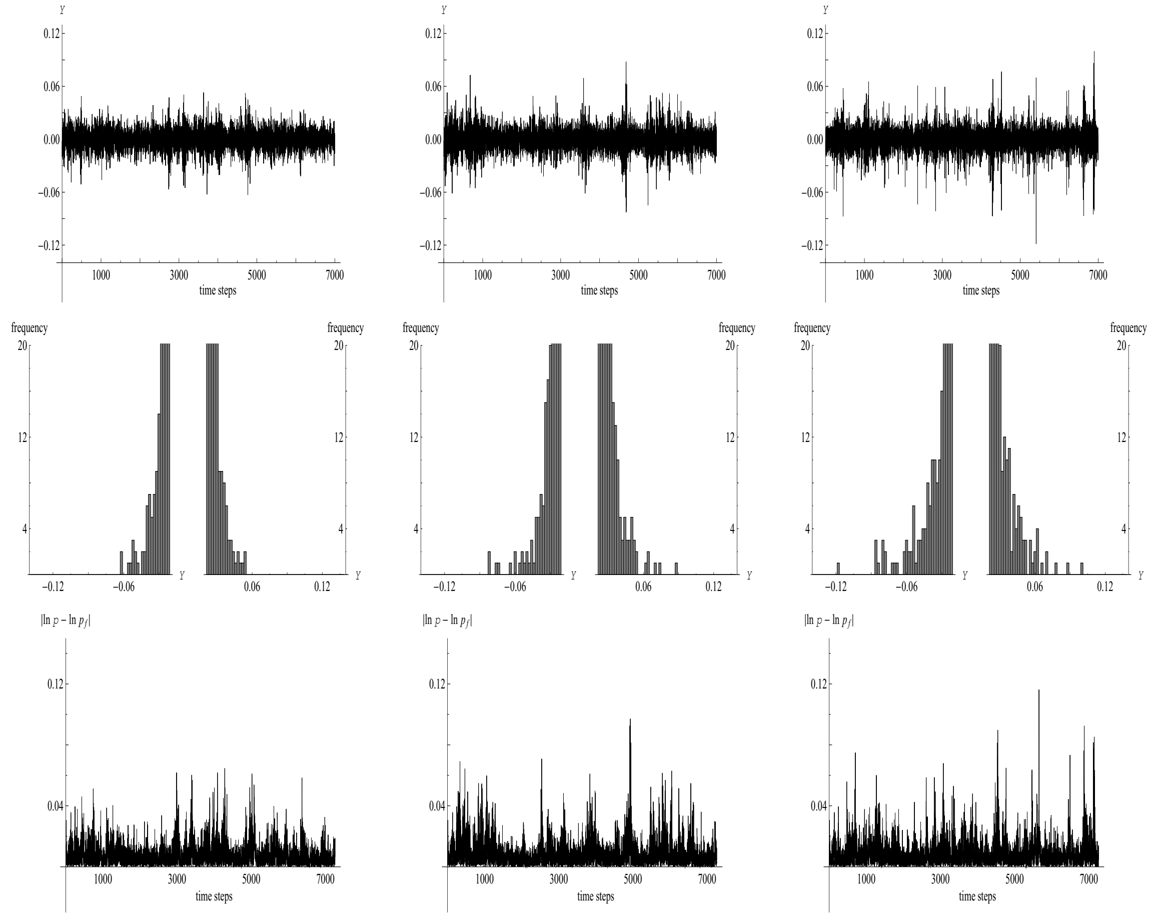

Figure 1: Destabilization of the financial market with an increase of the fraction of institutional investors

Left panels: the top panel presents the return series, whereas the middle panel shows the tails of the histogram of returns, and the bottom panel presents the volatility of the regulated situation for the basic model without regulations.

Middle panels: these panels are interpreted in the same way as the left panels, albeit for a 10% proportion of institutional investors.

Right panels: these panels are interpreted in the same way as the left and middle panels, albeit for a 40% proportion of institutional investors.

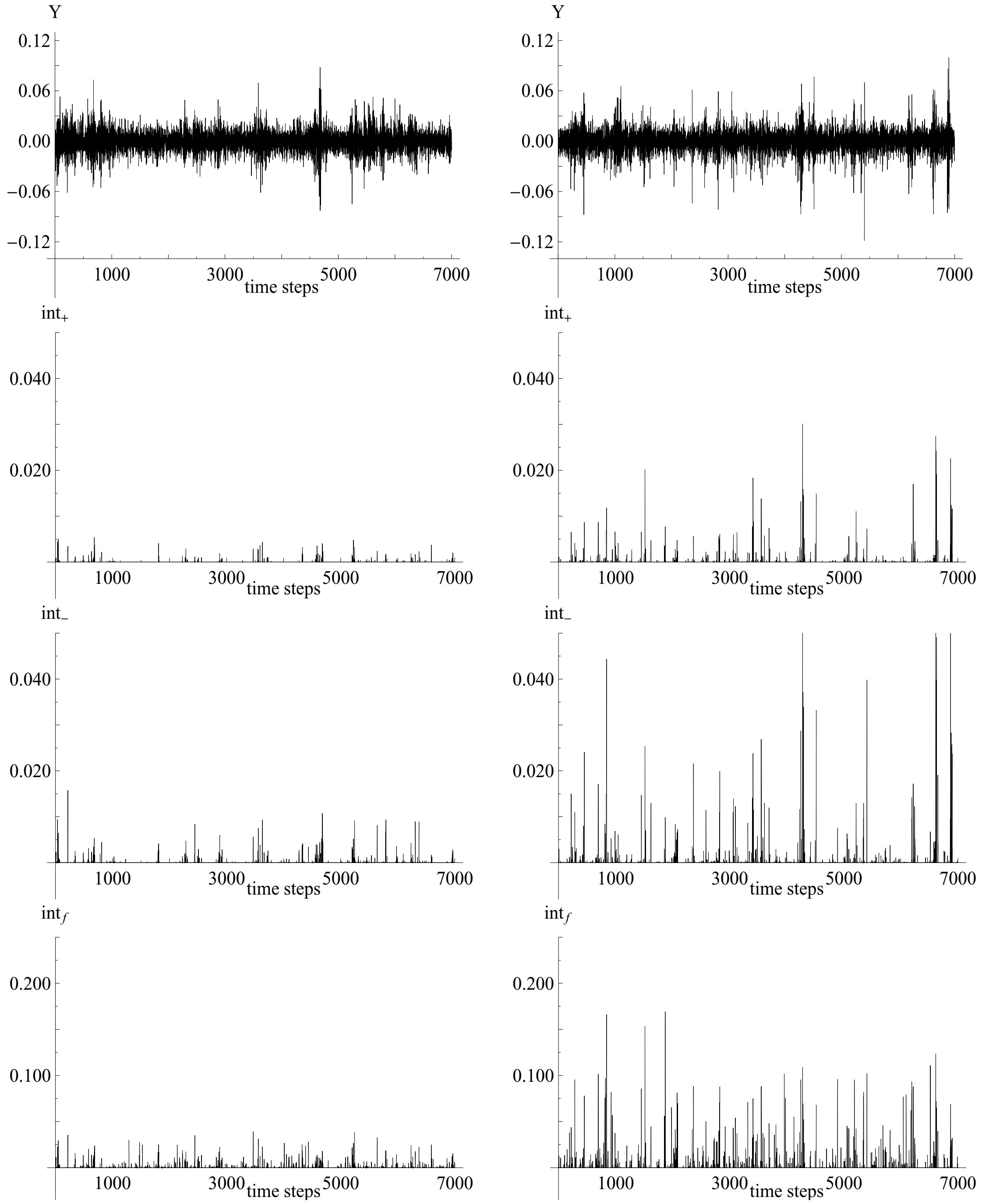

Figure 2: Analysis of transactions by institutional investors

Left panels: the top panel presents the return series for the regulated financial market with a proportion of 10% institutional investors. The following three panels show, from top to bottom, the proportion of optimistic chartists, pessimistic chartists and fundamentalists.
Right panels: these panels are interpreted in the same way as the middle panels, albeit for a 40% proportion of institutional investors.

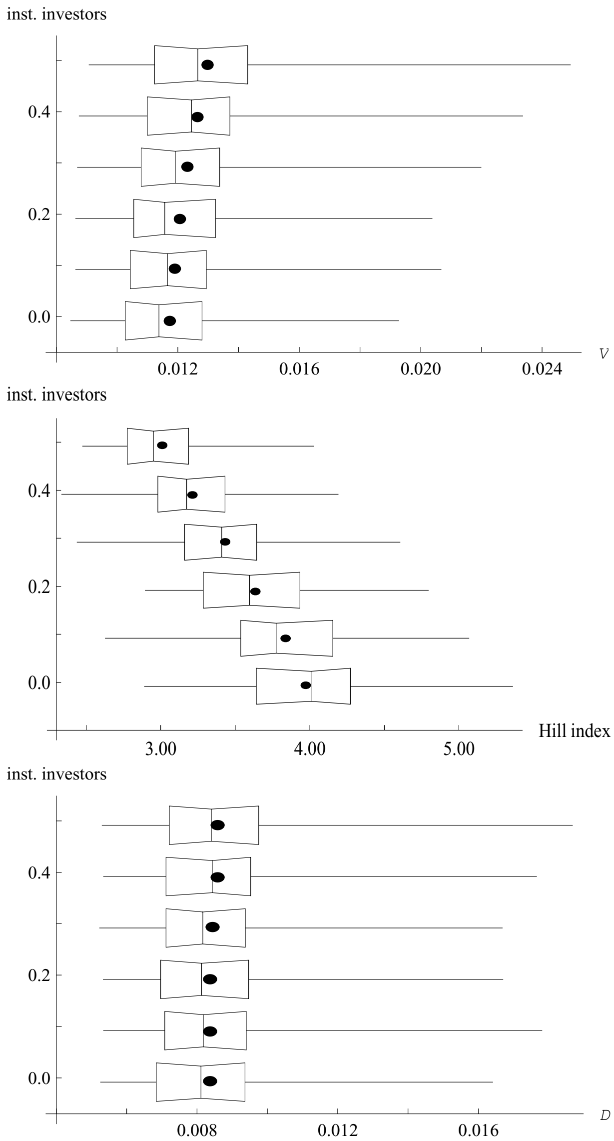

Figure 3: Results for the market stability measures

From top to bottom: results for the market stability parameters volatility, Hill index, and distortion
Top panel: the volatility for a proportion of 50% (top), 40%, 30%, 30% 10%, and 0% (bottom) institutional investors. The left side of the box represents the 25% quantile, the right the 75% quantile of the average volatility of the simulated time series. The horizontal line represents the range of the the minimum and maximum of all the 200 time series. The mid vertical line represents the median, whereas the black dot is the mean of the average volatility.
Mid and bottom panels: the same setup for the Hill index and distortion.

Does Basel III improve financial market stability? A comparison with the Basel II framework*

Oliver Hermsen†

Abstract

Using a financial market model with heterogeneous interacting agents, we compare the Basel II framework with the new Basel III framework. We find that the Basel III framework has a greater influence on financial market stability than the Basel II regulations. The reason is a renunciation of the strict concept of using the most recent observations to calculate the level of regulatory capital for market risk with the introduction of the stressed Value-at-Risk. Under usual conditions the Basel III framework leads to a stabilization of the financial market whereas more extreme events sometimes are possible. However, if a very high proportion of market participants are affected by regulations, the Basel III framework may lead to significantly more severe price reductions compared to the Basel II framework.

Keywords: heterogeneous agent model, Basel II/III, level of regulatory capital, bank regulation, Value-at-Risk models

JEL Classification:

G32 - Financial Risk and Risk Management; G38 - Government Policy and Regulation

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1 Introduction

In 2007, the subprime crisis led to one of the most dramatic financial crises in recent decades. The breakdown of financial institutions (Lehman and Kaupthing) and bailouts (Bear Stearns, AIG and Northern Rock) followed. Many decision makers in politics, economics and in the scientific community believe that funding problems or too low levels of regulatory capital could have been the driving force behind these financial institutions' financial problems (Portes 2008, Brunnermeier 2009, Shin 2009, Wellink 2011).

At the start of the financial crisis, the "International Convergence of Capital Measurement and Capital Standards" (Basel II) announced by the "Basel Committee on Banking Supervision" (BCBS) governed the calculation of regulatory capital (BCBS 2006). The Basel II framework was criticized for many reasons both prior to and especially during the financial crisis (Danielsson et al. 2001). The BCBS (2009) therefore raised the level of regulatory capital for market risk for financial institutions using an internal model (as most financial institutions do) by adding an additive term called the "stressed Value-at-Risk" (sVaR). Additionally, in the Basel III framework the overall level of regulatory capital was raised to achieve greater financial stability (BCBS 2010).

The effects of these changes are hard to analyze. There is no or little empirical data available since the changes will only become stepwise valid by 2013. Initial results with general equilibrium models indicate an improvement of key macroeconomic variables (Angelini et al. 2011).

However, many researchers have challenged the reliability of these models regarding the analysis of financial markets (Lux/Westerhoff 2009). It is virtually impossible to analyze the effects on financial markets by general equilibrium models due to the dynamic behavior of return time series provoking typical stylized facts of financial markets such as volatility clustering and heavy-tailed return distributions (McNeil et al. 2006, Chen et al. 2008). However, it is extremely important to analyze the Basel III framework with an instrument that is capable of replicating these specific attributes. We therefore use a heterogeneous agent model (HAM) introduced by Brock/Hommes (1998) and adjusted by Franke/Westerhoff (2011) to evaluate the possible effects caused by the above-mentioned adjustments of the Basel II framework.

Over the last decade, many issues of economic policy that greatly influence financial market stability such as the Tobin tax (Westerhoff/Dieci 2006; Mannaro et al. 2008), central bank interventions (Westerhoff 2003), shortselling issues (Anufriev/Tuinstra 2010) and the Basel II framework (Hermsen 2010b) have been investigated by HAMs. An overview about this strand of research can be found in Chiarella et al. (2009), Hommes (2006), LeBaron (2006), Lux (2009) and Westerhoff (2008).

Without doubt, the Basel frameworks have had a strong impact on financial markets. Financial institutions aim to have regulatory capital just above the minimum capital requirements, since regulatory capital is more expensive than loan capital. This effect will become even more marked because an additional new aspect of the Basel III framework is a strengthened capital base, which means that more (expensive) common equity must be part of the regulatory capital (Wellink 2011). If the necessary regulatory capital is too high above the minimal required regulatory capital, it might be the best way for financial institutions to sell risky assets to reduce the necessary regulatory capital. In other words, the Basel frameworks influence the demand of financial markets because some market participants are forced to trade on account of these regulations (Hermsen 2010b). The interesting question is whether the newly introduced instruments are able to stabilize financial markets more effectively than the Basel II framework, which was unable to cope with the challenges of the financial crisis. To be precise, in this paper we explore how financial market stability is influenced by the Basel III framework compared to the previously valid Basel II framework.

The remainder of the the paper is as follows. First, we include Basel II and III regulations into a heterogeneous agent mode by Franke and Westerhoff (2011). Section 3 explains how specific details of these frameworks are incorporated into this model and describes how the simulations were conducted. Sections 4 and 5 deal with the results of these simulations. Here, Section 4 takes one representative time series into account, whereas a Monte Carlo simulation with results for 100 time series is highlighted in Section 5. Section 6 discusses the results of the two previous sections, and Section 7 concludes the paper.

2 The model

The basic model used in this paper introduced by Franke/Westerhoff (2011) uses the Discrete Choice Approach of Brock/Hommes' model (1998). Franke/Westerhoff (2011) compare many heterogeneous agent models in their paper. Here, it was evaluated best regarding many stylized facts of financial markets, such as capturing volatility clustering, declining autocorrelation of squared returns, fat tails of the return distribution and a lack of autocorrelation of raw returns. Therefore, we choose this model for an implemention of the Basel II/III regulations. The procedure is similar as in Hermsen (2010b), although there the model by Lux/Marchesi was adjusted for the Basel II regulations in a similar way.

In Franke/Westerhoff's approach the price formation is modeled by a market maker balancing the weighted excess demand and supply of agents in the previous period d_{t-1}. We obtain

$$p_t = p_{t-1} + \mu \cdot d_{t-1} \tag{1}$$

with p_t as the logarithmic price on day t. Furthermore, it is dependent on the price of the previous day p_{t-1} and a constant factor μ. Excess demand d_t is defined as

$$d_t = n_t^f z_t^f + n_t^c z_t^c + n_t^{reg} z_t^{reg}. \tag{2}$$

We see that d_t is determined by the trading signals of the groups of fundamentalists and chartists z_t^f and z_t^c, respectively, weighted by group shares n_t^f and n_t^c, as in Franke/Westerhoff (2011). Additionally, the last term is necessary to add traders affected by regulations, called "regulated traders" (reg). If there is no need for regulation, the last term is omitted and formula (1) appears as in Franke/Westerhoff (2011). Their trading signal and weight is simultaneously modeled and denoted by z_t^{reg} and n_t^{reg}. We require the weighted demand in Section 5.1 to analyze the impact of regulated traders on the model dynamics. Hence, we additionally define the weighted demand for each group by

$$d_t^{f;c,reg} = n_t^{f;c,reg} \cdot z_t^{f;c;reg}. \tag{3}$$

Sales by regulated traders are "forced" sales. The regulatory authority forces agents who are actually convinced of fundamentalists' or chartists' trading strategies to sell assets.

Formulae for the chartists' and fundamentalists' trading signals remain the same as in the basic model, hence, we obtain

$$z_t^f = \phi(p^* - p_t) + \sigma_t^f \, \epsilon_t^f \text{ with } \epsilon_t^f \sim N(0,1) \tag{4}$$

$$z_t^c = \chi(p_t - p_{t-1}) + \sigma_t^c \epsilon_t^c \text{ with } \epsilon_t^c \sim N(0,1). \tag{5}$$

As in Franke/Westerhoff (2011), the fundamentalists' trading signal is positive/negative if the price is below/above the fundamental value p^* of the asset. The chartists' trading signal is positive/negative if the price trend increases/decreases. ϕ and χ are reaction parameters of the demand of fundamentalists and chartists. The noise terms capture deviations from the basic trading rules caused by individual divergences from the above trading rules, as substantiated in detail in Franke/Westerhoff (2011).

It is well known in the literature that both regulatory authorities and financial institutions define minimum limits $\mathrm{lrc}_{\mathrm{min}}$ for their level of regulatory capital. The Basel III framework, in particular, as an extension of the Basel II framework, uses an increase of these minimum limits as a method to extend the overall level of regulatory capital to avoid further financial crises such as those that occurred over the last five years. The formula of the trading signal of regulated traders is similar to the modeling of fundamentalists' demand. The demand generated by fundamentalists and regulated traders is dependent on the extent to which a certain threshold – fundamental price p^* for fundamentalists and the minimum level of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$ – is exceeded. We then compare them with the reference values – the price p for the fundamentalists and the level of regulatory capital $\mathrm{lrc}^{\mathrm{mr}}$ for regulated traders – to model the trading signal.

$$\begin{aligned} z_t^{reg} &= -\rho \frac{\mathrm{lrc}_{t-1}^{\mathrm{mr}} - \mathrm{lrc}_{\mathrm{min}}}{\mathrm{lrc}_{\mathrm{min}}} \text{ if } \mathrm{lrc}_{t-1}^{\mathrm{mr}} > \mathrm{lrc}_{\mathrm{min}} \\ z_t^{reg} &= 0 \text{ if } \mathrm{lrc}_{t-1}^{\mathrm{mr}} < \mathrm{lrc}_{\mathrm{min}} \end{aligned} \tag{6}$$

Figure 1 explains how the trading signal of regulated traders functions. If the minimum level of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$ is exceeded by the level of regulatory capital $\mathrm{lrc}^{\mathrm{mr}}$, calculated based on the portfolio held by the financial institution ($\mathrm{lrc}_{t-1}^{\mathrm{mr}} > \mathrm{lrc}_{\mathrm{min}}$), a fraction N^{reg} of regulated traders are not allowed to apply their usual trading rules, but have to sell risky assets from their portfolio. During time periods 7600 to 7900 and

8000 to 8250 in Figure 1, the gray shaded area marks the exceedance of lrc_{min} in the top panel. The consequence is that riskier assets are sold, shown in the bottom panel by the negative excess demand z^{reg} of regulated traders. Otherwise, regulated traders would be forced to generate more regulatory capital, which is quite expensive for a financial institution, especially in times of financial crises as we have seen (liquidity problems).

Figure 1 comes about here.

The more the limit is exceeded, the more riskier assets have to be sold to avoid an extensively high level of regulatory capital way above the minimum level of regulatory capital. In Figure 1, we recognize at the peaks for the time series of lrc^{mr} around time steps 7800 and 8100 in the top panel, the lowest values for the time series of z^{reg} in the bottom panel. Hence, the most risky assets are sold by regulated traders here.

If the level of regulatory capital is below the minimum capital requirements ($\text{lrc}^{\text{mr}}_{t-1} < \text{lrc}_{\text{min}}$) agents of the groups of fundamentalists and chartists follow the trading rules in which they believe and no legal restrictions have to be applied, since the necessary level of regulatory capital is below the minimum level of regulatory capital and, therefore, there is no tendency for banks to keep regulatory capital low. These periods are not marked in the top panel in Figure 1. Therefore, z^{reg} in the bottom panel is zero in periods without legal restrictions. We assume that at least the minimum level of regulatory capital is always held by a financial institution.

ρ in Formula (6) is chosen such that the overall absolute excess demand approximates a situation without regulation and is – due to the similarity of the fundamentalists' trading rules – in the simulations chosen with $\rho = \theta$ (cp. Formula (4)). Furthermore, we assume the proportion of chartists and fundamentalists affected by regulations to be equal.

According to Franke and Westerhoff's (2001) model, the weights of fundamentalism/chartism are determined by

$$\begin{aligned} n_t^{f,bel} &= \frac{1}{1 + \exp(-\beta a_{t-1})} \\ n_t^{c,bel} &= 1 - n_t^{f,bel} \end{aligned} \tag{7}$$

where β is the intensity of choice (Brock/Hommes 1998; Franke/Westerhoff 2011). In this formula, a_t is defined as

$$a_t = \alpha_n (n_t^{f,bel} - n_t^{c,bel}) + \alpha_0 + \alpha_p (p_t - p^*)^2. \tag{8}$$

Franke and Westerhoff (2001) call this formula the attractiveness index. In the HPM variation of their model chosen here, attractiveness is determined by agents' *h*erding behavior of the agents (first term), *p*redisposition of the former strategy (second term) and the *m*isalignment of the price (third term). $\alpha_n \geq 0$ and $\alpha_p \geq 0$ are strictly positive constants[1].

It is only important to know which trading rule the agents believe in (for this purpose, we add the suffix "bel" to $n_t^{f/c}$). If the risk of the portfolio is low and if only the minimum regulatory capital requirements are necessary ($\mathrm{lrc}_{t-1} < \mathrm{lrc}_{\mathrm{min}}$), the agents behave according to the trading rules of which they are convinced. If they use regulations, they are not convinced of this trading rule but have to apply regulations since the minimum level of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$ is exceeded by the level of regulatory capital $\mathrm{lrc}_t^{\mathrm{mr}}$, so there is $\mathrm{lrc}_{t-1}^{\mathrm{mr}} > \mathrm{lrc}_{\mathrm{min}}$. A special maximum proportion of regulated traders N^{reg} will sell risky assets to prevent a too high level of (expensive) regulatory capital. Why do we call this proportion the "maximum proportion"?

In this context, we have to be aware of one situation: if the agents want to sell more assets with the respective fundamentalists' or chartists' trading rules than with the regulated traders' trading rule or regulation ($z_t^{f,c} < z_t^{f,c}$), they behave according to their conviction and apply the "usual" trading rule, anyway. If fundamentalists/chartists wish to sell more assets, only a fraction $n_t^{reg} = n_t^{c/f} \cdot \mathrm{N}^{\mathrm{reg}}$ have to apply regulations. If both groups generate more excess demand than determined by regulated traders' rules, no regulations have to be applied ($n_t^{reg} = 0$). This leads to the following case distinction for

[1]Model modifications also explored in their paper led to relatively similar results for the Basel II/III regulations. Interesting contributions concerning herding behavior in agent-based models can be found in Irle et al. (2011) and Alfarano/Milaković (2009)

the weight of regulated traders n_t^{reg}:

$$
\begin{aligned}
n_t^{reg} &= \mathrm{N}^{\text{reg}} \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^c > z_t^{reg} \text{ and } z_t^f > z_t^{reg} \\
n_t^{reg} &= n_t^c \cdot \mathrm{N}^{\text{reg}} \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^c > z_t^{reg} \text{ and } z_t^f < z_t^{reg} \\
n_t^{reg} &= n_t^f \cdot \mathrm{N}^{\text{reg}} \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f > z_t^{reg} \\
n_t^{reg} &= 0 \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} < \mathrm{lrc}_{\text{min}} \text{ or} \\
&\qquad \text{if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f < z_t^{reg}.
\end{aligned}
\tag{9}
$$

To obtain the weights of the respective groups, we have to subtract the regulated traders from the other groups using the same distinction of cases as in Formula (9). We obtain

$$
\begin{aligned}
n_t^{f,c} &= n_t^{f,c,bel}(1 - n_t^{reg}) \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^{f,c} > z_t^{reg} \\
n_t^f &= n_t^{f,bel}(1 - n_t^{reg});\ n_t^c = n_t^{c,bel} \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^f > z_t^{reg} \text{ and } z_t^c < z_t^{reg} \\
n_t^c &= n_t^{c,bel}(1 - n_t^{reg});\ n_t^f = n_t^{f,bel} \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^f < z_t^{reg} \text{ and } z_t^c > z_t^{reg} \\
n_t^{f;c} &= 0 \text{ if } \mathrm{lrc}_{t-1}^{\text{mr}} < \mathrm{lrc}_{\text{min}} \text{ or} \\
&\qquad \text{if } \mathrm{lrc}_{t-1}^{\text{mr}} > \mathrm{lrc}_{\text{min}} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f < z_t^{reg}.
\end{aligned}
\tag{10}
$$

The model described here was also used in Hermsen (2011) to analyze specific aspects of Basel III which are not considered in the model comparison of this paper. In a synchronous manner, the model's equations of the Lux/Marchesi model (1999/2000) were extended by Basel II regulations in Hermsen (2010b).

Comparing the model used in this paper with that of Hermsen (2010b), we find a similar approach in both papers. However, the modeling of regulated traders' demand differs. This required a revision, due to the changes implemented from the Basel II to the Basel III framework, such as the stressed Value-at-Risk. How these changes are incorporated into the model described in this section and what differentiates them from Hermsen (2010b) is explained in the next section.

3 Consideration of the Basel II/III regulations and measurement of financial market stability

This section explains the changes that took place between the Basel II and the Basel III Capital Accord and how they are incorporated in the model presented in Section 2. Furthermore, an explanation is given of which Value-at-Risk models are used, why they were chosen, and how they have been integrated in the model. Finally, financial market stability is defined.

3.1 Changes in the Basel III Capital Accord concerning market risk

With a new construct called "stressed Value-at-Risk" (sVaR), the BCBS (2009, 718 LXXVi (k)) has reacted on the problems of financial market stability that occurred in 2007/8. It aims to compel financial institutions to hold a capital base and provide enough liquidity to enable them to balance their extraordinary losses in the event of a crash. The new formula for capital requirements for market risk c^{mr} is:

$$\begin{aligned} \mathrm{cr}_t^{\mathrm{mr}} = \max & \left(\tfrac{h}{60} \textstyle\sum_{i=1}^{60} \mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t) \right) + \\ \max & \left(\tfrac{h}{60} \textstyle\sum_{i=1}^{60} \mathrm{sVaR}_{0.99}(\mathbf{10}|t-i), \mathrm{sVaR}_{0.99}(\mathbf{10}|t) \right), \end{aligned} \tag{11}$$

where $\mathrm{VaR}_{0.99}(\mathbf{10}|t-i)$ is the 99%-VaR of the (cumulative) loss distribution of the next 10 periods (days), $\mathrm{sVaR}_{0.99}(\mathbf{10}|t-i)$ is the 99%-sVaR of the (cumulative) loss distribution of the next 10 periods (days), $\mathrm{cr}_t^{\mathrm{mr}}$ is the level of regulatory capital for market risk in the next period, and h is a multiplier. The multiplier is chosen from a range between $h = 3$ and $h = 4$. Financial institutions and the supervisory authority have to backtest that the VaR model used is suitable for capturing market risk. The backtesting procedure is performed for the 1-step-VaR $\mathrm{VaR}_{0.99}(1|t)$. h is raised dependent on the number of backtesting exceptions. A backtesting exception occurs when the loss is higher than the VaR on one day. In the Basel II and III frameworks, the model is categorized in the green zone for $h = 3$, in the yellow zone for $3 < h < 4$, and in the red zone for $h = 4$. Factor h is valid for both the first VaR part and the second sVaR part of (11) (BCBS 2006, 2009; Stahl 1998).

The second part of Equation (11) causes a significant increase in the level of regulatory capital for market risk (Bank of America 2010). The calculation for the stressed

Value-at-Risk (sVaR) is virtually the same as the VaR: only the time span for which the calculation takes places is different. Here BCBS (2009, p. 14) determines "historical data from a continuous 12-month period of significant financial stress relevant to the bank's portfolio" for the calculation. "As an example, for many portfolios, a 12-month period relating to significant losses in 2007/2008 would adequately reflect a period of such stress," BCBS 2009 (p. 14).

The stressed Value-at-Risk is one reason why it is necessary to change the modeling of regulated traders compared to Hermsen (2010b), where regulated traders become active at time steps with backtesting exceptions. With the stressed Value-at-Risk – due to the higher level of regulatory capital — the minimum level of regulatory capital is exceeded much more frequently than on trading days with extraordinary losses. Furthermore, the stressed Value-at-Risk is not dependent on the most recent observations. Here, using the dependence on the level of regulatory capital, we might be able to draw a more realistic picture of the effects of the Basel frameworks, especially Basel III. Beyond that, we need a common basis in which the same reference value is used for both frameworks. It made sense to apply $\mathrm{lrc}^{\mathrm{mr}}$ and $\mathrm{lrc}_{\mathrm{min}}$ which are relevant for each time step of both Basel II and III frameworks, instead of using backtesting exceptions, which are only relevant to the most recent observations since the importance of those observations declines in the Basel III framework.

The next change affecting both market risk and the other types of risk (credit risk and operational risk) inherent in the Basel II/III framework is the increase in the capital base. By 2019, the minimum level of regulatory capital or the minimum total capital ratio ($\mathrm{lrc}_{\mathrm{min}}$) will increase from 8% to 10.5%, an increase of 35% (BCBS 2010, Annex 4). Since it is hard to determine how this increase is apportioned to the particular risk types, we assume that $\mathrm{lrc}_{\mathrm{min}}$ will also be increased by this proportion. The level of regulatory capital for market risk $\mathrm{lrc}^{\mathrm{mr}}$ is then calculated by the quotient of the capital requirements for market risk $\mathrm{cr}_t^{\mathrm{mr}}$ and the assets connected to this risk type, here the portfolio value $\exp(p_t)$ (recall that p_t is the logarithmic price) that is

$$lrc_t^{\mathrm{mr}} = \frac{\mathrm{cr}_t^{\mathrm{mr}}}{\exp(p_t)}$$

.

It is easy to incorporate these changes into the model specified in Section 2. In our first simulation procedure, we employ the Basel II regulations, meaning that cr_t^{mr} is calculated using the first maximum expression of Equation (11) only. To analyze the changes in financial market stability defined at the end of this section, the same simulation procedure is carried out a second time using Equation (11), as defined in the Basel III framework. In the second run, the minimum level of regulatory capital lrc_{min} is raised by the respective factor, as determined in the Basel III framework.

3.2 Value-at-Risk models

First, we have to define the risk measure "Value-at-Risk". For this purpose, we use the α-quantile of the (cumulative) τ-step return distribution $Q_\alpha(\boldsymbol{\tau}|t)$[2]. According to Reiss/Thomas (2007), it is easy to calculate the 1-step or 10-step-Value-at-Risk as required for Formula (11) with this quantile

$$\text{VaR}_{1-\alpha}(\boldsymbol{\tau}|t) = \exp(p_t)\left(1 - \exp\left((Q_\alpha(\boldsymbol{\tau}|t)\right)\right). \tag{12}$$

We use the three Value-at-Risk models predominately used in practice (Homburg & Scherpereel 2006). These are VaR models with quite different, sometimes simple assumptions for the (cumulative) τ-step return distribution or the weighting of historical observations. In its recently revised framework concerning market risk the BCBS, for instance, still indirectly suggests historical volatility (BCBS 2009, 718 (LXXVI) c)) with the assumption of the normal distribution for the (cumulative) τ-step return distribution. The appendix provides a brief formal description of the models used.

We use these models because we wish to analyze the impact of regulations under relatively realistic conditions, in line with actual practice. Since these models were predominately used before and during the financial crisis we have applied them in this paper (Homburg & Scherpereel 2006, Marrison 2002). For the Basel II framework it is shown in Hermsen (2010a) that models with simple assumptions mainly lead to a lower lrc^{mr}, what could explain why financial institutions choose them.
Figure 2 provides an overview of the characteristics of the return time series of the basic

[2]The bold $\boldsymbol{\tau}$ in the formula symbolizes the return distribution for the time period from t to τ days. In the case of the Basel II/III framework, the BCBS prescribes $\boldsymbol{\tau} = 10$ days.

model and the respective level of regulatory capital. The top panels show the time series for the basic model when no regulated traders are included for the returns and $\mathrm{lrc}^{\mathrm{mr}}$. The $\mathrm{lrc}^{\mathrm{mr}}$ we identify for the Basel III framework compared to Basel II is over twice as large.

Figure 2 comes about here

The panels below describe these time series for each specific VaR model. The second row of panels show the respective series using historical volatility (hv). Compared to the top, first row of panels, additionally, the VaR estimates are presented by the black solid line in the right-hand panel. The left panels show the minimum required levels of regulatory capital for the Basel II framework (solid horizontal line) which is 35% higher for the Basel III framework (dotted horizontal line). This increase is obviously unable to compensate for the increase resulting from the additional stressed VaR. Since the minimum required $\mathrm{lrc}_{\mathrm{min}}$ is exceeded much more frequently for the Basel III framework, regulated traders will attempt to sell risky assets more frequently to lower their $\mathrm{lrc}^{\mathrm{mr}}$ down to near $\mathrm{lrc}_{\mathrm{min}}$.

The third respectively forth row of panels show the same as for the second row of panels, albeit for historical simulation (hs) and the exponential weighted moving average model (ew). Hereby, we identify a lower level of regulatory capital for banks using the EWMA model compared to historical volatility and simulation, which is in line with Hermsen (2010a). We also observe that the ups and downs of the time series are relatively similar regardless which model is used and although the VaR estimates differ to a certain extent (cp. left-hand panels). Since we assume that a third of all banks use each model, the overall $\mathrm{lrc}^{\mathrm{mr}}$ is calculated by weighting the level of regulatory capital calculated for each model $\mathrm{lrc}^{\mathrm{hv;hs;ew}}$ by $1/3$. This leads to the following specification of $N^{reg} = \mathrm{N}^{hv} + \mathrm{N}^{hs} + \mathrm{N}^{ew}$ of Equation (9)

$$\begin{aligned} \mathrm{N}^{hv;hs;ew} &= \frac{1}{3}\mathrm{N}^{\mathrm{reg}} \text{ if } \mathrm{lrc}_{t-1}^{hv;hs;ew} > \mathrm{lrc}_{\mathrm{min}} \\ \mathrm{N}^{hv;hs;ew} &= 0 \text{ if } \mathrm{lrc}_{t-1}^{hv;hs;ew} < \mathrm{lrc}_{\mathrm{min}}. \end{aligned} \tag{13}$$

In this formula, N^{hv} denotes regulated traders using historical volatility, whereas N^{hs} and N^{ew} denote the same albeit for historical simulation and the EWMA model. The associated level of regulatory capital for market risk determined by the respective method is denoted by $\mathrm{lrc}_t^{hv;hs;ew}$. We see that the assumed maximum proportion of regulated traders N^{reg} is only obtained on trading days for which all VaR models exceed lrc_{min}, and chartists and fundamentalists do not wish to sell more assets than a regulated trader is forced to sell.

The impact of using other VaR models on the stability of financial markets when applying Basel III regulations shall be left as a subject of further research. How financial market stability is measured will be explained in the next subsection.

3.3 Simulation details

In the Monte Carlo simulations, we use 100 time series. Each time series consists of 11,500 time steps. The first 1320 observations are not considered in the results of the Monte Carlo simulation, since we need a starting period to calculate the VaR and, especially, the stressed VaR.[3]

The constants and parameters of the model are taken from Franke/Westerhoff (2011), who fitted the model such that it is able to replicate the stylized facts of financial markets. The only new constant ρ is due to the similarity in construction of the fundamentalists' and regulated traders' trading rules with the fundamentalists' trading rule (cp. Formulae (4) and (9))[4]. Hence, we assume $\rho = \theta$. Furthermore, we use the same random variables to analyze the Basel II and Basel III frameworks to enable the results to be compared directly. This way, we are able to identify concrete differences and similarities with regard to how the different frameworks cope in specific situations (sudden crashes, volatility clusters, or also "calm" periods).

We use a "rolling analysis" to calculate the Value-at-Risk, stressed Value-at-Risk and, hence, also the capital requirements and level of regulatory capital.[5] Every day, the last value of a period of one year is excluded and a new value included. The next values for VaR, sVaR, and $\mathrm{lrc}^{\mathrm{mr}}$ are calculated for the new period . The "period of stress" used for the calculation of the stressed Value-at-Risk is chosen by determining the standard

[3] Additionally, we need VaR estimators of one year to be able to calculate the LRC

[4] These values are $p^* = 0, \phi = 0.12, \chi = 1.5, \alpha_0 = -0.336, \alpha_n = 1.839, \alpha_p = 19.671, \sigma^f = 0.708, \sigma^c = 2.147$ and the reaction parameter of the regulated traders $\rho = 0.12$.

[5] According to BCBS (2011b), different methods can be used to calculate Value-at-Risk and stressed Value-at-Risk. In the paper, we always use the same method to calculate both VaR and stressed VaR. Since the results do not differ considerably regarding stressed Value-at-Risk, this assumption does not affect the results significantly.

deviation of one quarter every day. If the new value is higher than the previously used "period of stress", the period is taken as the new "period of stress". Thus, this period does not change very often in the simulations of 11,500 time steps which leads to a relatively constant sVaR over time. This procedure is in line with the description given in BCBS (2011a, 10.2.).

3.4 Defining financial market stability

We use three key measures to characterize financial market stability similarly applied in Westerhoff (2008), Demary (2011) and Hermsen et al. (2010): volatility, distortion, and the Hill index. All three measures are important to gain an overview of some of the key attributes as described in the following paragraphs.

Volatility is characterized by

$$V = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \overline{Y}\right)^2} \tag{14}$$

as the standard deviation of returns with $Y_t = p_t - p_{t-1}$. The lower the volatility, the lower the overall average amplitude of returns. It is obvious that a low degree of volatility has a stabilizing effect on financial markets.

Distortion is defined as

$$D = \frac{1}{T}\sum_{t=1}^{T} \mid p_t - p_t^* \mid . \tag{15}$$

It is the mean absolute deviation between the realized log price and the log fundamental price. It can be used as a stabilization measure from the viewpoint of information efficiency. If the price is considerably above/below the fundamental value that is to represent all relevant information of the share/index, many agents become fundamentalists and push the price back quite rapidly to its fundamental value. Hence, a high distortion indicates a high risk of bubbles/crashes occurring in the financial market.

To determine the Hill tail index H, we have to arrange the absolute returns in an descending order $\mid Y_T \mid > \mid Y_{T-1} \mid > \cdots > \mid Y_{t-k} \mid > \cdots > \mid Y_1 \mid$ where k is the number of returns considered in the tail of the distribution. Then we obtain α^H where

$$\alpha^H = \left(\frac{1}{k} \sum_{i=1}^{k} (\mid Y_{T-i+1} \mid - \mid Y_{T-k} \mid) \right)^{-1}. \tag{16}$$

2.5% or 5% are possible tail factions (Lux/Ausloos 2002). In the simulations, we set k at 5% of the tails' observations. The floor of the tail index indicates the number of existing moments. Hence, the tail index is an appropriate measure to determine the existence of extremal returns indicating extraordinary losses. Extraordinary losses are considered specifically problematic to financial institutions by the BCBS (2006) and Brunnermeier (2009) since they often instigate changes in banks' regulatory capital and, hence, may cause portfolio adjustments due to higher future volatility.

The three stabilization measures – volatility, distortion, and the Hill tail index – are used to assess financial market stability for the Monte Carlo simulation in Section 5.

4 Analysis of selected time series

In this section, we illustrate the consequences of the regulations for one representative time series. This is important to identify specific aspects of the impact of these regulations. A more general analysis is subsequently conducted by means of a Monte Carlo simulation in Section 5.

Figure 3 compares the Basel II and III frameworks. In the left-hand panels, this aspect is investigated for a fraction of maximum 2% of transactions by regulated traders per day; in the right-hand panels, this fraction is raised to 4%. Note that the effective trade of regulated traders is significantly lower. This is shown in the next section.

Figure 3 comes about here

Even if we allow a relatively low maximum proportion of regulated traders per day of 2% (left-hand panels), we see a profound change in the time series. Whereas the time series of the logarithmic prices (top panel) seems to be virtually the same for the Basel II (solid line) and Basel III (dotted line) frameworks, there are obvious differences in the returns time series (middle panels). The maximum amplitude of the volatility clusters decrease for the Basel III framework between time steps 2000 and 5000. This observation is even more significant for $N^{\text{reg}} = 4\%$ (right-hand panels). Here, the fluctuations in the logarithmic prices (top panel) are also clearly identifiable[6].

However, there are also volatility clusters for which the number of maximum returns increases considerably for the Basel III framework, such as for the volatility cluster around time step 6500 in both the left- and right-hand panels. Furthermore, quite large negative sporadic extreme returns occur before time steps 4000 and 8000 (right mid-bottom panel for 4% maximum trades a day).

Comparing the level of regulatory capital according to Basel II/III for market risk (bottom panels), we identify a clear increase in the Basel III framework due to the stressed Value-at-Risk. Considering this large change in the lrc^{mr}, we would have expected a more significant change in the return time series. Furthermore, the higher N^{reg} does not affect the lrc^{mr}.

If we increase N^{reg} to higher levels of 5%, 10% or even 15%, we obtain an even more stabilized financial market with lower volatility, distortion and extraordinary events on most trading days. However, in extreme situations, these higher maximum fractions of regulated traders can cause a very severe crash. In the 100 time series of the Monte Carlo simulations with 10,000 observations, only 4 exhibit such a severe crash for $N^{\text{reg}} = 15\%$. One such time series is depicted in Figure 4, which explains how the weights of the different groups of fundamentalists, chartists and regulated traders must develop for a crash to occur.

Figure 4 comes about here

Looking at the left-hand panels, we recognize quite normal model dynamics for $N^{\text{reg}} = 5\%$. The weights of fundamentalists and chartists fluctuate quite normally, which becomes apparent when comparing the dynamics of the Basel III framework (gray line) with the dynamics of the Basel II framework which are virtually unaffected by the regulations (cp. Figure 3). Of course, the same is true for $N^{\text{reg}} = 2\%$ and 4%, as presented in Figure 3 above.

Increasing N^{reg} to 10% means that regulated traders gain more influence (bottom

[6]Further explanations of economic behavior follow in connection with Figure 4 and for the Monte Carlo simulation in Figure 5.

middle panel). We obtain a higher negative excess demand by regulated traders especially for time series, which cause a high level of regulation capital $\mathrm{lrc}^{\mathrm{mr}}$, as depicted here. This drives the price further away from the fundamental price. The consequence is that more and more traders who are unaffected by regulations become fundamentalists. This, in turn, leads to a stabilization of the financial market. However, this stabilization has an imminent danger, as we will see when considering $N^{\mathrm{reg}} = 15\%$.

For this very high maximum fraction of regulated traders we obtain a severe crash as visualized in the right-hand panels. This crash is due to the design of the regulations assessed by the BCBS. We should explore the definition of the level of regulatory capital as the quotient of capital requirements and the portfolio's value. Here the numerator increases due to the price crash (the Value-at-Risk increases due to the crash). At the same time, the price – hence the assets' value – decreases on account of the crash. This leads to a very sharp increase in the level of regulatory capital, enabling regulated traders to sell more and more assets (bottom right panel). The chartists become crowd out of the market (mid-bottom panel); the weight and associated excess demand of the fundamentalists is too weak to compensate for the excess demand of regulated traders[7]. It is a vicious circle that ends up in a complete price crash. In extreme situations, we see that a too strictly regulated financial market may lead to a complete loss of assets for our model, caused by the regulation rules.

To sum up the results of this section for low to medium fractions of regulated traders, we identify a low stabilization of the financial market concerning volatility. However, the amplitude of some volatility clusters increases compared to the Basel II framework. These may even lead to a destabilization in certain situations. These aspects and the role of extraordinary losses are investigated in the Monte Carlo simulation in the next section. Furthermore, we must be aware that higher fractions of regulated traders may cause a strong stabilization of the financial market. The problem is that this can lead to a very severe crash with a complete price decay in extreme situations.

[7]The excess demand of the respective group is analyzed in the Monte Carlo simulation in the next section

5 Monte Carlo simulation

In this section we analyze 100 time series, as described in the previous section. Here, we first focus on how the dynamics of the model is affected. Then, we analyze financial market stability with the market stability measures (cp. Section 3.3). Finally, the risk measures Value-at-Risk and stressed Value-at-Risk are investigated concerning their influence on the capital requirements, cr^{mr}, and the level of regulatory capital, $\mathrm{lrc}^{\mathrm{mr}}$.

5.1 Model analysis

Analyzing the effects of regulations z^{reg} on the model parameters, they have a very different impact, dependent on the framework considered. Recall that we merely integrated the new term concerning the calculation of regulatory capital for market risk (cp. Equation (11)) and the increase in overall regulatory capital. Equations that affect our model are not changed in any sense.

The boxplots of Figure 5 can be interpreted as follow: the left- and right-hand borders of the box represent the 25% and 75% percentile of the 100 time series. The vertical line in the box is the median of the stability measures' values and the point is the mean of the observations. The horizontal line shows the range of the respective measures' values.

Figure 5 shows an almost constant weighted excess demand for the Basel II framework (left-hand panels). The reason is that the higher excess demand of fundamentalists is leveled out by the lower excess demand of chartists for the higher maximum proportion of regulated traders shown in the mid-left panels. The trade of regulated traders is minimal, and can virtually be neglected.

Figure 5 comes about here

These effects change considering the Basel III regulations in the right-hand panels of Figure 5. The adjusted calculation of the $\mathrm{lrc}^{\mathrm{mr}}$ and the higher levels of regulatory capital have a considerably greater impact on the model. Since results are constant for varying N^{reg} for the Basel II framework, this is mainly a result of the new maximum expression of Equation (11). Its effect on the level of regulatory capital is analyzed in greater detail in Section 5.3.

For the Basel III framework, the effect of the lower excess demand of chartists and regulated traders is greater than the increased excess demand of the fundamentalists which lead to an overall slight negative excess demand d (cp. Formula (3)). We can conclude that the Basel III regulations are a deeper intervention in the mechanism of the financial market simulated using Franke/Westerhoffs' model (2011). For the Basel II regulations, the dynamics of the model balanced the "unsymmetrical" new regulation rule, which was not the case for the new regulations of the Basel III framework.

5.2 Market stability

Analyzing Figure 6, we identify a clear difference concerning the Basel II and III frameworks. For the currently valid Basel II framework (cp. left-hand panels), volatility and distortion decline marginally (if we can identify a decline at all) with increasing proportions of transactions by regulated traders. For the Basel III framework, we notice a clear decline in volatility and distortion levels. This is quite positive. It seems that the new Basel III regulations do indeed stabilize financial markets

Figure 6 comes about here

However, the bottom panels of Figure 6 offer a different view of the problem. They show a decline in the Hill index for $1\% \leq N^{\text{reg}} \leq 7.5\%$, meaning that there are more extraordinary events with relatively high gains and losses for the new Basel III framework, whereas no effects can be identified for the Basel II framework. This is a negative aspect, since these are events that cause financial institutions difficulties. If the maximum proportion of regulated traders increases, this effect is weakened or diminishes completely.

The fact that a destabilization for the Basel III framework is also possible compared to the basic model or the Basel II regulated model is supported by Table 1. Here we compare the results for each value of the stability measures for each time series of the Monte Carlo simulation with three reference values.

The first reference value of the top part of Table 1 is the mean of the basic time series without any regulation for volatility, distortion, and the Hill tail index. For the Basel II framework, we cannot identify any pronounced changes concerning the stability measures (top lines for each stability measure). For the basic time series without regulation (meaning 0% of maximum proportion of regulated traders), 48 (volatility), 49 (distortion), and 46 (Hill tail index) of each of the 100 time series provided higher means than the average mean of all of the 100 time series. These values do not change significantly. Only for the distortion, the values of 41 and 36 for $N^{\max} = 7.5\%$ and 10% indicate a slight decrease. Together with the boxplots of the left-hand panels in Figure 6, we cannot identify any clear influence of the Basel II regulations on financial market stability.

In contrast, we recognize a clear stabilization concerning volatility and – even more significantly – concerning distortion for the Basel III framework (bottom lines for each stability measure). For instance, assuming $N^{\max} = 4\%$, only 20% of the time series' mean for volatility and 10% for distortion in the Monte Carlo simulation indicate destabilization. Concerning the Hill tail index, the result is not that clear. For fractions of $N^{\max} = 2\%$ to 5%, the Hill tail index decreases, indicating an increase in extraordinary profits or losses. This observation is not as pronounced as for the Basel II framework. However, for a higher fraction of maximum transactions by regulated traders, this observation changes again.

Since we used the same random variables for the different time series, it is also quite relevant to compare the values for the stability measures for each time series with the results if the fraction of maximum transactions by regulated traders, $N^{\max}$, is raised. It is interesting to see whether a destabilization of the financial market may occur for increasing $N^{\max}$. We compare each value for the stability measures of $N^{\max} = 1\%$ to 10% with the respective value of the basic time series ($N^{\max} = 0\%$). This comparison is presented in the middle part of Table 1. Since it makes no sense to compare the basic time series with the basic time series there is no value in this part of Table 1.

Even for volatility in the Basel II framework we identify a stabilization, which is again more profound for the Basel III framework. For the distortion, we see a clear stabilization for both frameworks. To interpret one value for the Basel II framework, the 1 for a proportion of $N^{\max} = 4\%$ means that the distortion for 99 of the 100 time series was lower in the time series with a maximum proportion of 4% of regulated traders compared to the basic time series simulated with the same random variables for the noise terms. For the Hill tail index, we are unable to identify a clear tendency for the Basel II framework. For the Basel III framework, we can interpret the results in the same way than for the top part. However, the results are somewhat less profound as for the top part of the table.

In the bottom part of Table 1, we compare both frameworks directly. For this purpose, we compare the values of the Basel II framework of one time series with the direct counterpart of the Basel III framework, simulated using the same random variables for the noise terms. Since we compare both frameworks here, only one row for each stability measure is presented. To interpret one value, the 22 for a proportion of $N^{\max} = 4\%$ means that for 22 of 100 time series, volatility was lower in the Basel II framework than the respective value for the same maximum proportion of regulated traders in the Basel III framework. To interpret the results for volatility, there is a tendency especially for low proportions of $N^{\max}$ for the Basel III framework to provide lower volatility. However, it can also be the case that lower values for volatility and, hence, a greater stabilization of the financial market concerning this stability measure, occur for the Basel II framework. For higher proportions of $N^{\max}$, this possibility is reduced.

For distortion, in turn, the result is unambiguous. For all of the time series for all proportions of $N^{\max}$, Basel III leads to less distortion and, hence, to a stabilization of the financial market. For the Hill tail index, we identify between 2% and 5% lower values for the Hill tail index for proportions of $N^{\max}$, meaning more extraordinary profits and losses for the Basel III framework. To interpret this, we recognize even greater volatility for the Basel III framework for some time series (for instance, exactly 22 for volatility and 32 for the Hill tail index for our previously chosen example of $N^{\max} = 4\%$). This mainly happens if one or two volatility clusters become much large in amplitude, whereas other volatility clusters of the time series shrink or disappear, as seen in Figure 2 in Section 4. From an economic perspective, this means a stabilization of the financial market for many time periods. However, a quite severe crisis with a large amount of extraordinary losses can also happen sometimes with the Basel III framework. However, this effect diminishes for higher proportions and even changes directions for a proportion of 10%.

However, a further increase of $N^{\max}$ is not the way to obtain a perfect stabilized financial market with the Basel III framework (as seen in Section 4). For higher proportions of $N^{\max}$ from 12% and above, the increasing negative average excess demand of regulated traders (cp. Section 5.1; top panels of Figure 5) leads to a continuous price crash. Then, the value of the portfolio converts to zero which is, of course, not a desirable target for regulators. For the stability measures, we obtain very high values for the distortion, zero volatility and no extraordinary profits and losses. For the Basel II framework, this price behavior can be observed for (unrealistically) high proportions.

5.3 Specific effects of Basel III

Analyzing Figure 7, we first identify a decline in one- and ten-step VaR. We can explain this by the lower standard deviation for Basel III time series. The extraordinary losses captured by the Hill tail index are not included because they are losses below the 1% quantile (here, other risk measures that capture the downsize risk might be necessary, cp. Yamai/Yoshiba 2002a/b, Artzner et al. 1999).

Another problem becomes apparent when juxtaposing the Value-at-Risk values of the first three rows of panels of Figure 8 used to calculate $\mathrm{cr}^{\mathrm{mr}}$ (cp. Formula (11)) with the value of the level of regulatory capital ($\mathrm{lrc}^{\mathrm{mr}}$). Although the risk measure indicates a significant reduction of risk with increasing $\mathrm{N}^{\mathrm{reg}}$, the required level of regulatory capital remains stable or even increases slightly, as the bottom panels indicate. However, we also identify a decrease in the capital requirements $\mathrm{cr}^{\mathrm{mr}}$, as the mid-bottom panels indicate[8].

The reason for the comparatively constant level of regulatory capital $\mathrm{lrc}^{\mathrm{mr}}$ (bottom panels) for the Basel III framework is that the value of the assets or portfolio, represented in the paper by price p (cp. top panels of Figure 3), declines. Therefore, the quotient of the capital requirements and the portfolio value constituting $\mathrm{lrc}^{\mathrm{mr}}$ (cp. Section 3.1) is quite constant.

6 Discussion

In this section we link the results and observations for one single time series of Section 4 and for the Monte Carlo simulation of Section 5. It does not matter whether we consider a single time series (Section 4), parts of the model, the stability parameters or the risk measure VaR with the level of regulatory capital. The main result is: the Basel III framework is a more severe intervention in the dynamics of the financial market than the Basel II framework. If the number of financial market transactions by regulated traders which are affected by regulations remains at an acceptable level, it could be an instrument to stabilize financial market fluctuations.

[8] We present results for historical simulation. Results for historical volatility and the EWMA model are quite similar.

Then, the distortion of the financial market, in particular, can be reduced. Concerning volatility, all values indicate a reduction for the Basel III framework, on average. However, an increase in volatility, especially during volatility clusters, is not impossible in certain situations (cp. Table 1 or Figure 2). This is also supported by the results for the Hill tail index, which for all comparisons of Table 1 and the boxplots of Figure 6 (Section 5.2) indicates an increase in extraordinary profits and losses for lower maximum proportions by regulated traders.

Section 5.3 reveals that the overall increase in the level of regulatory capital and the introduction of the stressed Value-at-Risk in addition to the Value-at-Risk leads to a lower consideration of the most recent values of a time series, hence, to the most recent risk situation. Both changes work like two constants which are attached to the "old" regulatory capital according to Basel II. Comparing both frameworks, it becomes apparent that the reduction in volatility and distortion in the Basel III framework leads additionally to a reduction in large price movements which may happen, but not that frequently. The consequence is a reduction in the price or portfolio value. Therefore, the level of regulatory capital is quite the same in the Basel III framework compared to the Basel II framework. This has both advantages and disadvantages. One advantage might be that the capital base is strengthend. For the same value of the Value-at-Risk, more than twice the amount of regulatory capital must be held by the financial institutions. However, neither a realistic picture of the present risk associated with the situation on the financial market can be deviated by the level of regulatory capital (one possibility for externals to obtain this information) nor can the financial market be influenced such that a crash can be prevented if a downturn of the price occurs.

7 Conclusion

We analyzed how financial market stability is influenced by the Basel III framework compared to the previously valid Basel II framework. For this purpose, we integrated crucial aspects of the Basel III framework regarding market risk in a heterogeneous agent model. These aspects are primarily the stressed Value-at-Risk, used additionally to determine the level of regulatory capital for market risk, and the raised minimum level of regulatory capital. The simulations indicate that the use of the stressed Value-at-Risk is a renunciation of the strictly Value-at-Risk-based framework, which aims solely to adequately capture the risk situation of a recent period. Indeed, the denotation of the stressed Value-at-Risk is similar, but its effect cannot be compared to that associated with the Value-at-Risk. In principle, the stressed Value-at-Risk works like a constant added to the level of regulatory capital, due to the generally constant period of stress. This means that the risk situation of the most recent observations does not affect the regulatory capital for market risk as much as in the Basel II framework.

The result is that the Basel III framework influences the dynamics of the financial market of our model much more than the Basel II framework, which was standard during the financial crisis that started in 2007. The integrated changes are able to reduce volatility and distortion significantly for low and medium maximum proportions of regulated traders in the market. For low proportions, however, we find more extraordinary losses and profits in some time series of the Monte Carlo simulation. One problem is that for very high proportions of regulated traders, strong price cuts occur for the Basel III framework, whereas the Basel II framework leads to a stable financial market. If regulators keep the proportion of regulated traders at a considerable level, the Basel III framework can be quite an adequate instrument to stabilize financial markets more than the Basel II framework, for which virtually no stabilizing effect could be found in the analysis.

Possible challenges for further research on this topic are widespread. From an empirical point of view, it might be interesting to explore the real proportion of regulated traders in the market. Then, it might be possible to adjust the model such that the fractions influencing the degree of (de-)stabilization can be modeled in step with actual conditions.

Other interesting questions for future research are to explore whether the transition period from the Basel II framework to the Basel III framework with constantly increasing minimum levels of regulatory capital leads to problems with the dynamics. Additionally, the same methodology can be used to explore whether additional proposals, such as countercyclical buffers, lead to a greater stabilization of financial markets. Another aspect might be to explore how the interaction of the level of regulatory capital of the different risk types might affect financial market stability. To solve this problem, we have to find a model that adequately combines credit, market, and operational risk. A third idea might be to test whether other more sophisticated Value-at-Risk models such as GARCH models which are actually not widespread in practice, may lead to greater stabilization at financial markets.

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Appendix: Value-at-Risk models

Historical volatility approach (hv)

The historical volatility is mentioned in both Basel II and III frameworks. We use the square root of time rule, which implies the quite simple assumption of $u_i = \sigma\epsilon_i$ with $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$ for the residuals of the return time series (BCBS 2006, 2009, 718 (LXXVI) (c) and (f)); Danielsson et al. 1998). We calculate the returns y_i by

$$y_i = \mu + u_i. \tag{17}$$

This means an equal treatment or weighting of past time steps with no consideration of volatility clusters. The additivity property of the normal distribution enables the calculation of the α-quantile by

$$Q_\alpha(\boldsymbol{\tau}|t) = \tau\mu + z_\alpha\sqrt{\tau}\sigma. \tag{18}$$

where z_α is the α-quantile of the standard normal distribution. We estimate μ and σ from the historical observations. The Value-at-Risk is then calculated using Formula (12).

Historical simulation (hs)

The returns of a time series with historical observations of daily returns are arranged in descending order, applying historical simulation. The α-quantile of $y_{(n)}, y_{(n-1)}, \ldots, y_{(n\ (1-\alpha))}, \ldots, y_{(1)}$ where $y_{(n)} \leq \ldots \leq y_{(1)}$, which we use to determine $\text{VaR}_\alpha(1|t)$, is the smallest value $y_{(n\ (1-\alpha))}$ not exceeding $n\ (1-\alpha)$, so that

$$Q_\alpha(1|t) = y_{(n\ (1-\alpha))}. \tag{19}$$

We have to determine the 10-step return distribution from the daily returns. For this purpose, we use a bootstrap approach with $\tau \cdot 5000$ observations to calculate the τ-step VaR. The quantile $Q_\alpha(\boldsymbol{\tau}|t)$ of the 10-step return distribution to obtain $\text{VaR}_\alpha(\boldsymbol{\tau}|t)$ can be determined from the 5000 cumulated ten-step returns in an analogous manner to that in (19). Then Formula (12) is reapplied.

Exponential weighted moving average (EWMA) approach (ew)

Zangari (1996) suggested using the exponential weighted moving average model (EWMA) which is another approach often applied by financial institutions (Holton 2003). The idea is to place greater weight on the most recent observation. In the basic model

$$y_i = \mu + u_i \text{ with } u_i = \sigma_i \epsilon_i \text{ and } \epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1),\ i = 1, \ldots, t-1, t, \tag{20}$$

the conditional volatility at time t is constructed by

$$E[u_{i+1}^2 | t] = E[(y_{i+1} - \mu)^2 | t] = h_t \text{ with } \widehat{h}_{1|t} = (1-\lambda) u_t^2 + \lambda \widehat{h}_t. \tag{21}$$

To estimate the one-step VaR, we apply the usual value $\lambda = 0.94$. If we replace σ^2 by time-dependent $\widehat{h}_{1|t}$ and assume that $\mu = 0$, we obtain

$$\widehat{y}_{1|t} \sim \mathcal{N}(0, \widehat{h}_{1|t}) \text{ and } \frac{\widehat{y}_{1|t}}{\sqrt{\widehat{h}_{1|t}}} \sim \mathcal{N}(0,1),$$

respectively, and further $Q_\alpha(1|t) = z_\alpha \sqrt{\widehat{h}_{1|t}}$.

$\widehat{h}_{1|t}$ is the best estimation for $u_{t+\tau}$. Hence, for the quantile of the 10-step distribution we obtain

$$Q_\alpha(\boldsymbol{\tau}|t) = z_\alpha \sqrt{\tau \widehat{h}_{1|t}}.$$

$\text{VaR}_\alpha(\boldsymbol{\tau}|t)$ is calculated using Formula (12).

Comparison with the mean of the basic time series									
Stability measure	Basel	N^{reg} 0%	1%	2%	3%	4%	5%	7.5%	10%
Volatility	II	48	48	48	47	45	46	44	44
	III	48	41	35	27	20	12	3	0
Distortion	II	49	47	45	44	44	43	41	36
	III	49	38	26	15	10	7	1	1
Hill tail index	II	46	45	45	46	48	47	47	47
	III	46	41	32	33	31	25	44	62
Comparison with the respective value of the basic time series									
Stability measure	Basel	N^{reg} 0%	1%	2%	3%	4%	5%	7.5%	10%
Volatility	II	xx	33	35	29	27	25	25	31
	III	xx	27	23	21	20	12	3	1
Distortion	II	xx	1	1	1	1	1	1	1
	III	xx	0	0	0	0	0	0	0
Hill tail index	II	xx	48	49	51	46	47	49	50
	III	xx	45	35	40	38	37	42	64
Comparison of the respective values of the Basel II and III framework									
Stability measure	Basel	N^{reg} 0%	1%	2%	3%	4%	5%	7.5%	10%
Volatility	xx	xx	27	22	23	22	12	3	1
Distortion	xx	xx	0	0	0	0	0	0	0
Hill tail index	xx	xx	47	36	36	32	32	42	65

Table 1: Results of the Monte Carlo simulation for the stability measures for Basel II and III

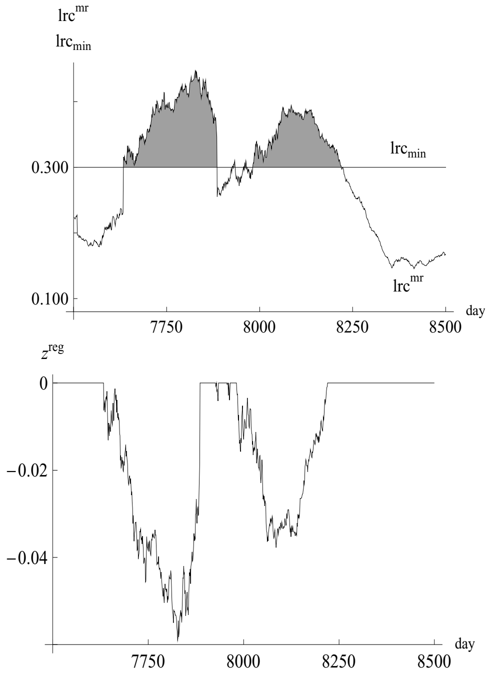

Figure 1: Generation of the excess demand of regulated traders z^{reg}
Top panel: Detail of the time series of the level of regulatory capital ($\mathrm{lrc}_t^{\mathrm{mr}}$) and the minimum level of regulatory capital ($\mathrm{lrc}_{\mathrm{min}}$).
Bottom panel: Detail of the time series of regulated traders' excess demand (z^{reg}) resulting from $\mathrm{lrc}_{\mathrm{min}}$ and $\mathrm{lrc}_t^{\mathrm{mr}}$ from the top panel.

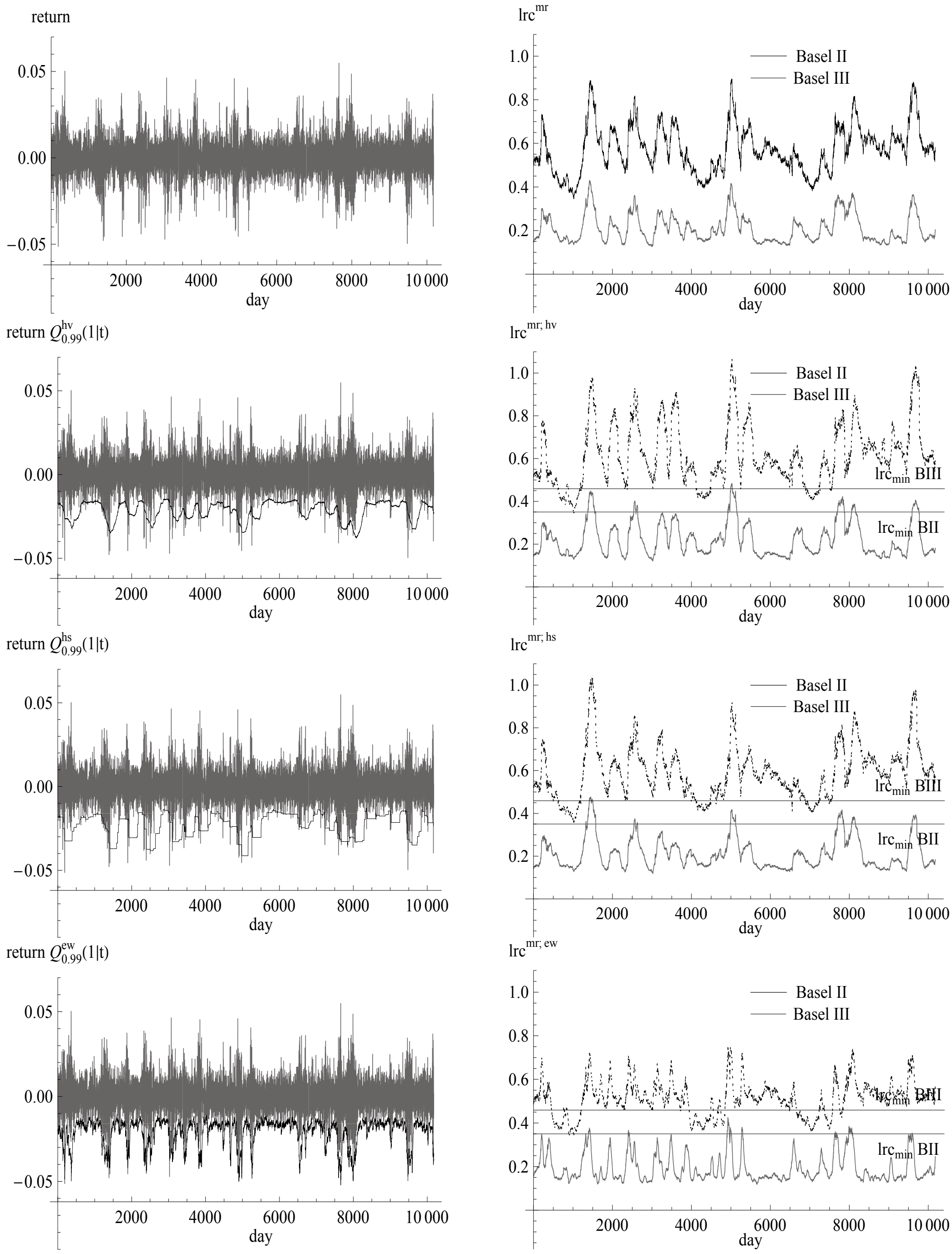

Figure 2: Return series (right panels) and series of the regulatory capital (left panels) for the basic model without regulated traders

Top panels: The return series and the respective regulatory capital for Basel II (gray line) and Basel III (black dotted line).
Mid-top panels: these panels are interpreted in the same way as the left-hand panels. Additionally, the time series of VaR estimates (black solid line) for regulated traders using historical volatility is shown in the right-hand panel. The left-hand panel shows the regulatory capital for regulated traders using historical volatility.
Mid-bottom panels: these panels are interpreted in the same way as the mid-top panels, albeit for regulated traders using historical simulation.
Bottom panels: these panels are interpreted in the same way as the mid-top panels, albeit for regulated traders using the EWMA approach.

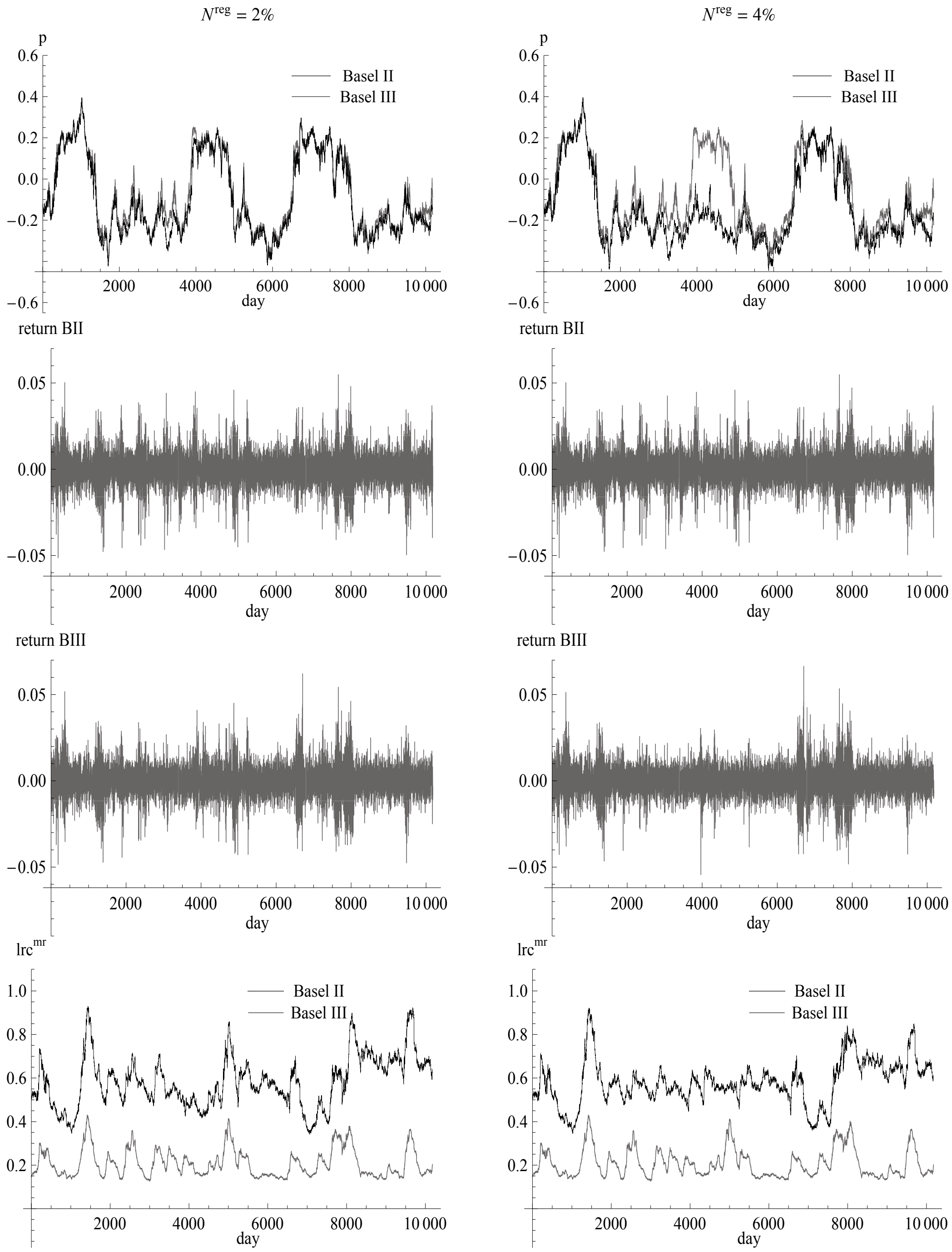

Figure 3: Comparison of the price, the return time series and the series of the level of regulatory capital for the Basel II and Basel III framework for a fraction of potential regulated traders' transactions of 2% (left) and 4% (right)

Top panels: Price time series for the Basel II framework (gray solid line) and the Basel III framework (dotted line) for a fraction of potential regulated traders' transactions of 2% (left) and 4% (right).
Mid-top panels: Return time series for the Basel II framework for the same fraction as for the top panels.
Mid-bottom panels: these panels are interpreted in the same way as the mid-top panels, albeit for the Basel III framework.
Bottom panels: these panels are interpreted in the same way as the top panels, albeit for the time series of the regulatory capital.

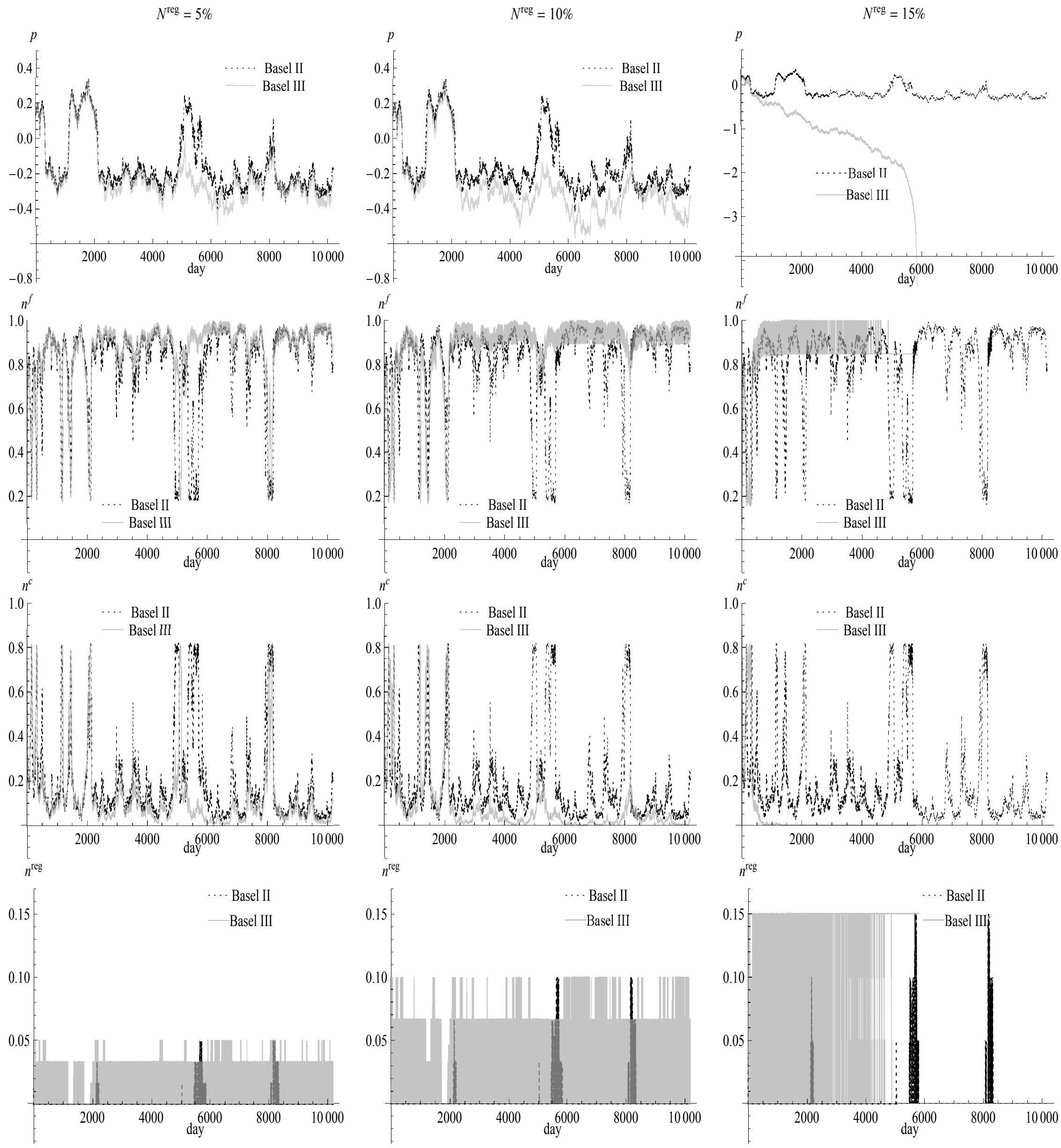

Figure 4: Analysis of the effect of an increase of N^{reg} from 5% to 15%

Top panels: from left to right the panels present the time series of log-price p of the Basel II (black, dotted) and Basel III (gray) framework for a maximum fraction of 5%, 10%, and 15% of regulated traders.
Mid-top panels: these panels are interpreted in the same way as the top panels, albeit for the weight of fundamentalists n^f.
Mid-bottom panels: these panels are interpreted in the same way as the top panels, albeit for the weight of chartists n^c.
Bottom panels: these panels are interpreted in the same way as the top panels, albeit for the weight of regulated traders n^{reg}.

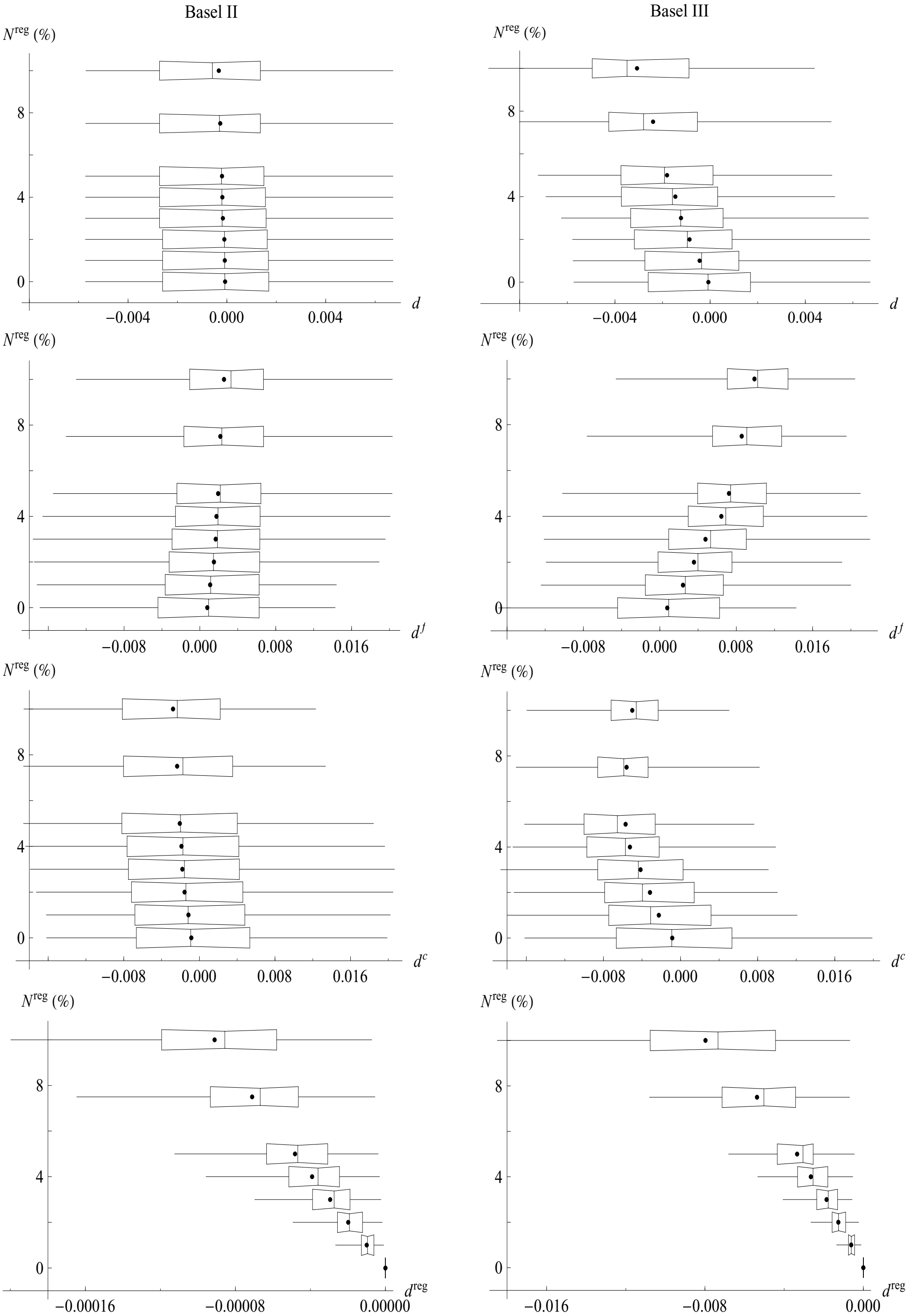

Figure 5: Development of the excess demand of the model with the increase in the fraction of potential trade by regulated traders

Left panels for the Basel II framework: the top panel presents the boxplots for the time series of the Monte Carlo simulation for – from top to bottom – the overall excess demand, excess demand of fundamentalists, excess demand of chartists, and excess demand of regulated traders.
Right panels: these panels are interpreted in the same way as the left-hand panels, albeit for the Basel III framework.

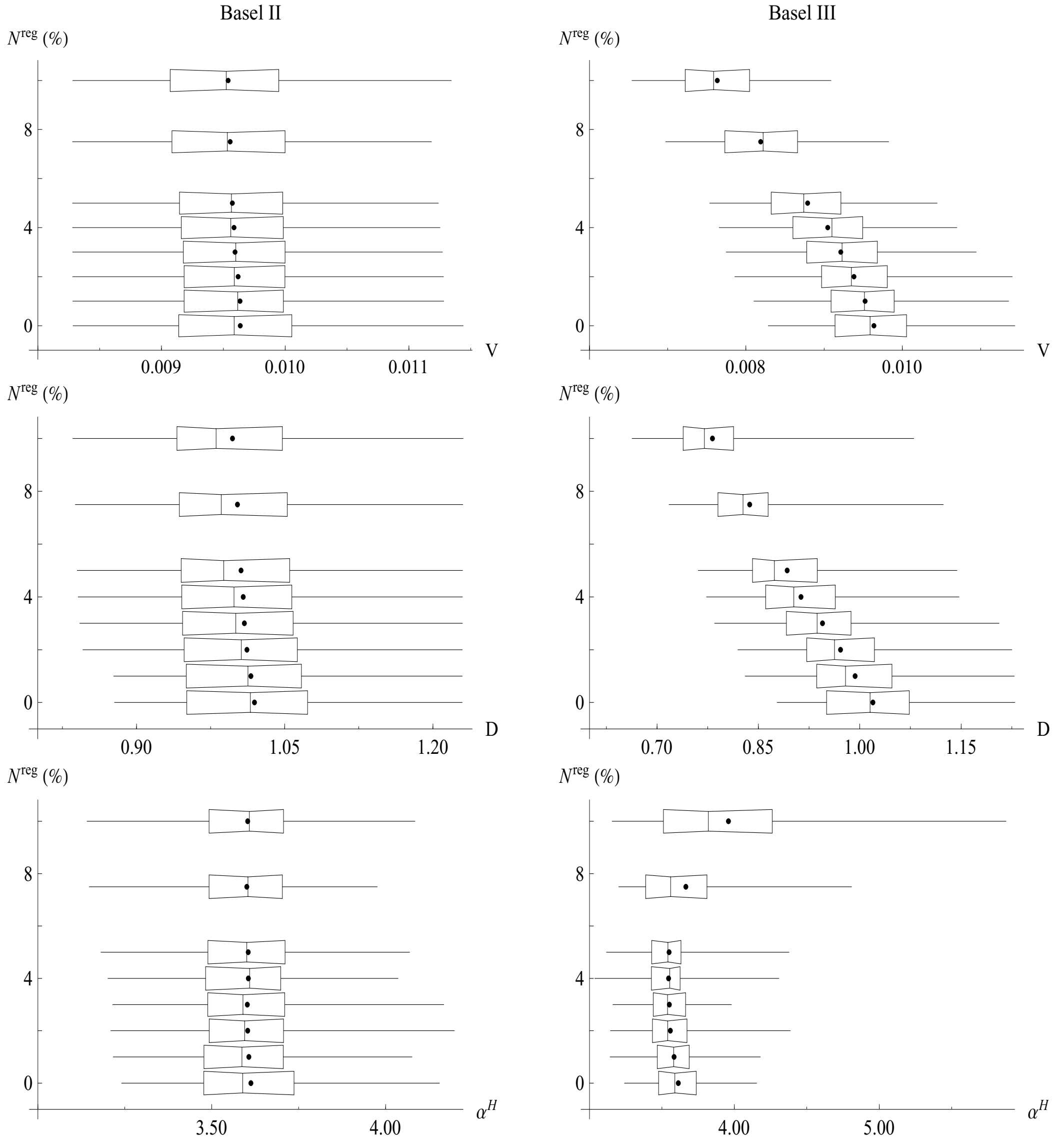

Figure 6: Reaction of stability measures with varying N^{reg}

Left panels for the Basel II framework: the top panel presents the boxplots for the time series of the Monte Carlo simulation for volatility, the middle panel for the distortion, and the bottom panel for the Hill tail index.
Right panels: these panels are interpreted in the same way as the left panels, albeit for the Basel III framework.

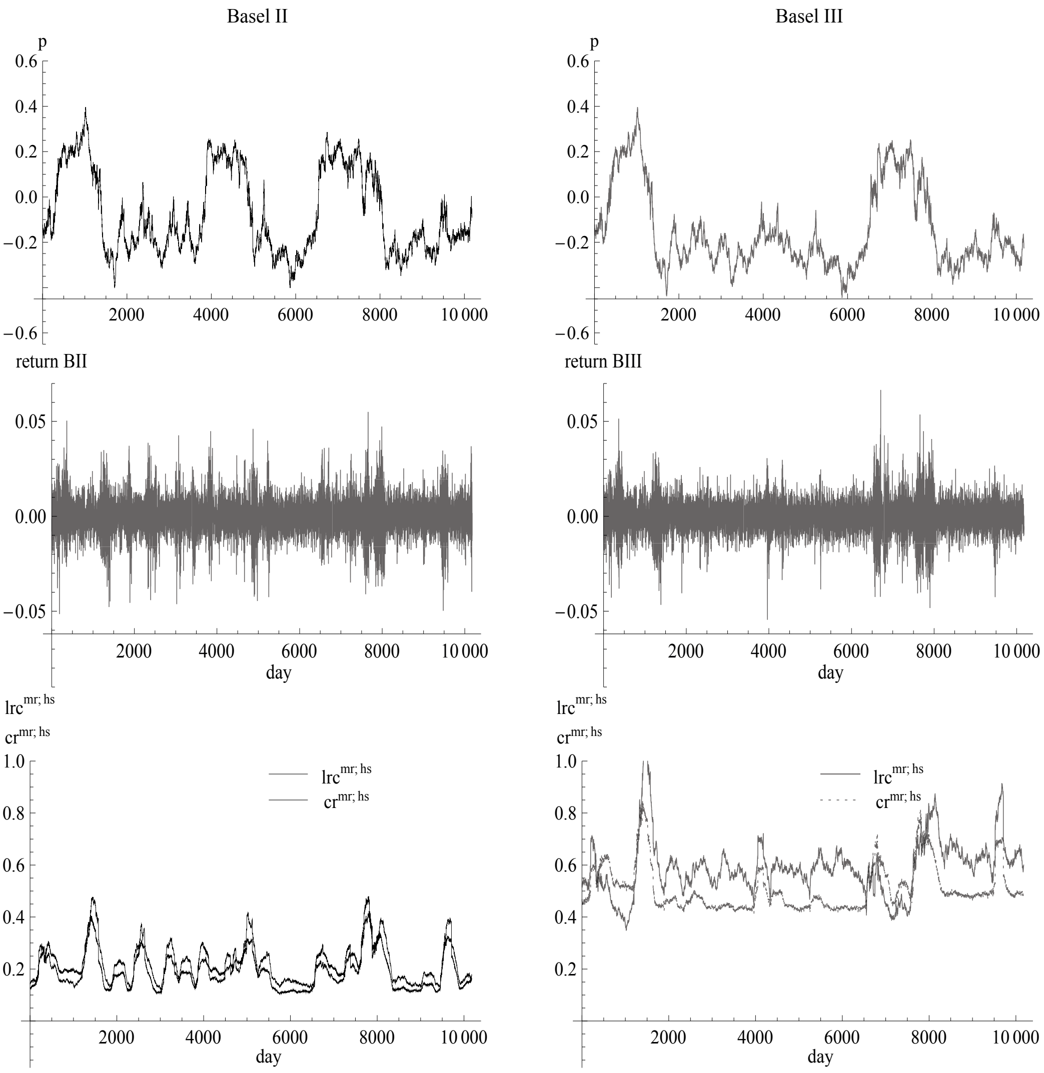

Figure 7: Analysis of the relative (solid) and absolute level (dotted) of regulatory capital

Left panels for the Basel II framework: the top panel presents the time series for the price level, the middle panel for the returns, and the bottom panel for the absolute and relative level of regulatory capital.
Right panels: these panels are interpreted in the same way as the left panels, albeit for the Basel III framework.

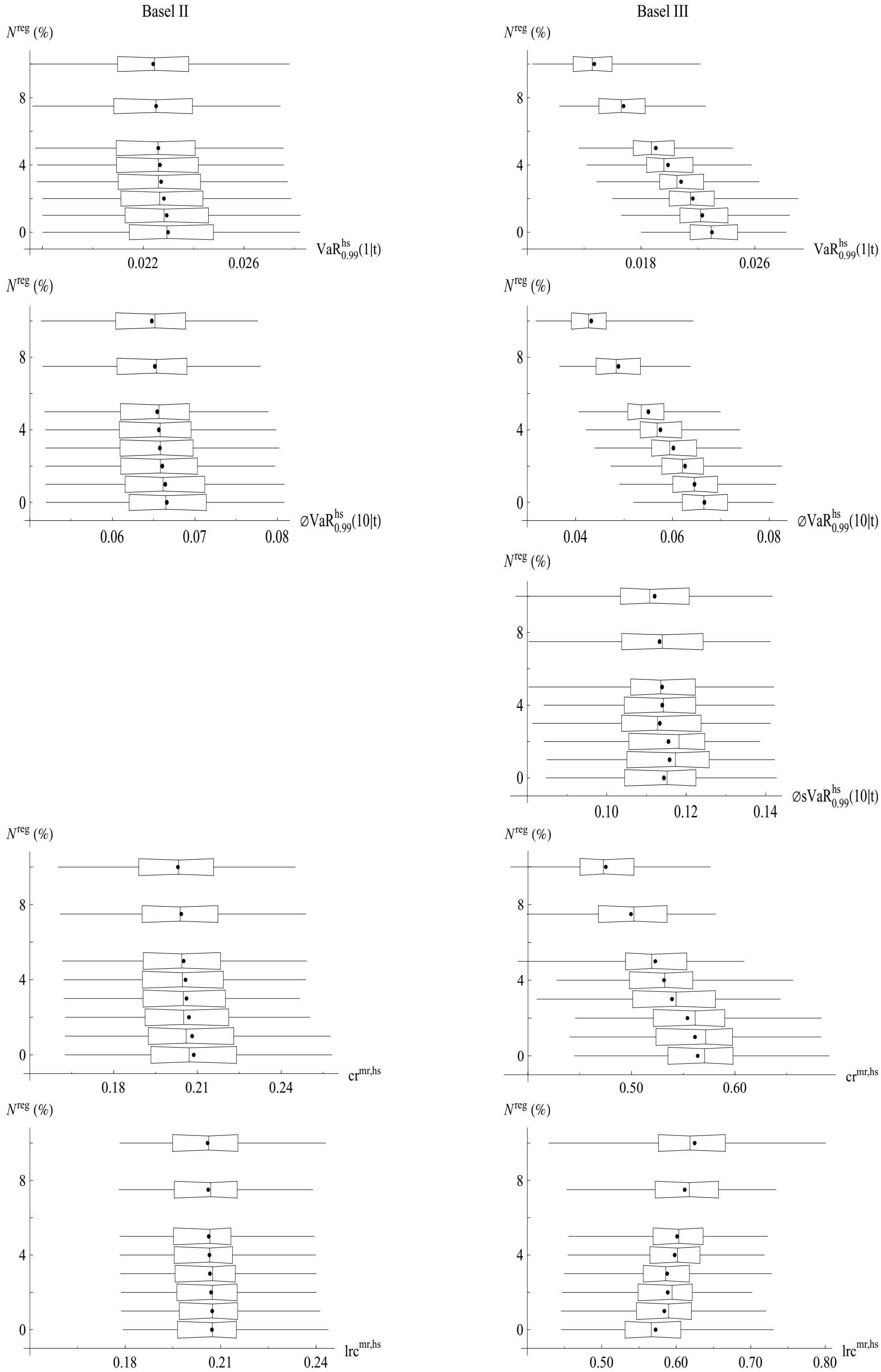

Figure 8: Analysis of impact of the risk measures on the level of regulatory capital

Left panels for the Basel II framework: from top to bottom, the panels present the boxplots for the time series of the Monte Carlo simulation for the 1-step Value-at-Risk, the 60-day average of the 10-step VaR, the 60-day average of the stressed 10-step VaR, the capital requirements (cr^{mr}) and the level of regulatory capital lrc (lrc^{mr}).
Right panels: these panels are interpreted in the same way as the left panels, albeit for the Basel III framework.

Effects of the new capital requirements of Basel III on financial market stability*

Oliver Hermsen†

Abstract

The Basel Committee on Banking Supervision has proposed several new instruments to obtain higher financial stability in the Basel III framework. The stressed Value-at-Risk aims to increase the level of regulation capital for market risk for a given portfolio held by a financial institution. Capital conservation and countercyclical buffers raise the minimum level of regulation capital for all risk types of the Basel III framework (credit, market, and operational risk). Our numerical analysis to study these instruments is based on a heterogeneous agent model. It reveals that the stressed Value-at-Risk stabilizes financial markets. The other instruments are unable to achieve this target.

Keywords: Value-at-Risk models, stressed Value-at-Risk, Basel III, level of regulatory capital, bank regulation, heterogeneous agent model
JEL Classification:
G32 - Financial Risk and Risk Management; G38 - Government Policy and Regulation

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1 Introduction

In this paper, we analyze the effects on financial market stability of the stressed Value-at-Risk, the capital conservation buffer, the countercyclical buffer, and the transition period as determined in the Basel III framework. It is shown by a heterogeneous agent model that the stressed Value-at-Risk has a strong positive effect on financial market stability. In turn, however both the conservation buffer and the countercyclical buffer cause destabilization. The influence of these two instruments is weaker than that resulting from stressed Value-at-Risk. The long transition period has no further influence on financial market stability.

The financial crisis that commenced in 2007 brought to light significant deficits in the calculation of regulatory capital. Breakdowns of financial institutions due to wrong risk assessments as seen for Lehman, formerly assessed as ”too big to fail”, or the Kaupthing bank revealed shortcomings in the rules used to calculate regulatory capital, thus, the Basel II regulations (Acharya et al. 2009).

The Basel Committee on Banking Supervision (BCBS) determined a set of rules concerning market risk to enable financial institutions to better withstand similar financial crises. The main target of these rules is ”to improve the banking’s sector ability to absorb shocks arising from financial and economic stress, whatever the source [...]” (BCBS 2011a, 1. p.1). The increase in the minimum level regulatory capital, partly with a capital conservation buffer and a countercyclical buffer is the core element of these rules. The transition period to implement these rules spans seven years, from 2013 to 2019.

Although some of these methods are more intended to strengthen the regulatory capital associated with credit risk, the structure of the Basel II/III framework had a direct effect on the other risk groups (market risk and operational risk). The overall level of regulatory capital consists of the sum of the level of regulatory capital of credit, market, and operational risk. Hence, if one position of these risk types, such as credit risk, increases, the financial institution could try to lower the level of regulatory capital for another risk type, e.g. market risk, to keep the overall level of regulatory capital low. The reason is that regulatory capital is much more expensive to acquire than loan capital. Hence, rules that mainly affect one risk group also have an indirect effect on the other risk groups within the framework (BCBS 2006, Crouhy et al. 2006).

The first change following the 2007 financial crisis which can directly be associated with market risk was the introduction of the stressed Value-at-Risk. With this new risk measure, the formula for determining market risk was adjusted (BCBS 2009). Here, instead of increasing *minimal* capital requirements, as for capital conservation and the countercyclical buffer, this instrument raises the necessary level of regulatory capital associated with a portfolio held by the financial institution. This change affects the capital requirements for market risk for a given portfolio to a large extent since it approximately doubles it (Bank of America 2010; Hermsen 2011).

Concerning the analysis of all these changes, it is crucial to analyze them implemented together; however, the impact of single effects is also interesting. A possible instrument for such an analysis are heterogeneous agent models (HAMs), as described comprehensively in Lux (2009), LeBaron (2006), Hommes (2006), Chiarella et al. (2009) and Westerhoff (2008). Former European Central Bank President Jean-Claude Trichet (2010) highlighted the opportunities and challenges involved in this approach compared to existing approaches during the financial crisis: "When the crisis came, the serious limitations of existing economic and financial models immediately became apparent. [...] I[i]n the face of the crisis, we felt abandoned by conventional tools." Focusing on HAMs, he continued: "We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. [...] Agent-based modelling dispenses with the optimisation assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention," Trichet (2010).

Furthermore, heterogeneous agent models are especially appropriate when there is a lack of empirical data which is obvious for the analysis of the effects of the Basel III framework because it will not be implemented by 2013. Furthermore, no time series of an appropriate length for longitudinal studies will be available in the first few years after its implementation.

HAMs have proven reliable in other topics, such as the Tobin tax (Westerhoff/Dieci 2006; Mannaro et al. 2008), central bank interventions (Westerhoff 2003) or the Basel II/III framework (Hermsen 2010, 2011). For the present analysis we use the Discrete Choice Approach (DCA), first introduced in the context of a financial market model by Brock/Hommes (1998) which was evaluated best concerning the ability to reproduce stylized facts of financial markets by Franke/Westerhoff (2011). We test the described changes step by step with the model and analyze which of them is able to guarantee more financial stability, as postulated by the BCBS (2011a, 1-3), and which of them are unsuitable.

The remainder of the paper is as follows. First, we define financial market stability with three well-known measures. Then, we describe the model in which the Basel III regulations are integrated. In the next section, we explain how specific details of the stressed Value-at-Risk, the conservation buffer, the countercyclical buffer, and the transition period are incorporated into the model and the simulation analyses. Afterwards, we present the result of these analyses for each of these instruments and combinations of them. Here, we use both results for one representative time series and a Monte Carlo simulation of 100 time series. Section 6 concludes the paper.

2 Financial market stability

Defining financial market stability means capturing and measuring key elements of a typical financial market time series. The same and similar measures are suggested for policy analyses in Westerhoff (2008), Hermsen et al. (2010) and Demary (2011). We need stability measures that describe the amplitude of returns $Y_t = p_t - p_{t-1}$ with p_t as the log-price of a portfolio. For this purpose, we use volatility

$$V = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \overline{Y}\right)^2}. \tag{1}$$

as the perhaps most well-used measure to characterize financial market stability. High returns indicate an up and down of prices and, hence, turbulences in the financial markets (Westerhoff 2008). Hence, a lower volatility is an indicator of a more stable financial market.

The second measure is the distortion of a financial market. Unpredictable and frequent disconnections of the price from the underlying fundamentals are indicators for bubbles and crashes on financial markets. These disconnections are defined as

$$D = \frac{1}{T}\sum_{t=1}^{T} \mid p_t - p_t^* \mid, \tag{2}$$

where p_t^* is the fundamental price. The higher the price is above or below the fundamental price the more likely is a sharp price correction back to the fundamental price will occur. Hence, a lower distortion indicates a more stable financial market (Westerhoff 2008).

A third measure is required to capture extreme price changes. To calculate the Hill tail index α^H we arrange returns in descending order $Y_T > Y_{T-1} > \cdots > Y_{t-k} > \cdots > Y_1$, where k is the number of returns considered in the tail of the distribution. We then obtain the Hill tail index by

$$\alpha^H = \left(\frac{1}{k} \sum_{i=1}^{k} (\ln \mid Y_{T-i+1} \mid - \ln \mid Y_{T-k} \mid) \right)^{-1}, \tag{3}$$

with possible tail fractions of 2.5% and 5% (Lux/Ausloos 2002). The floor of the Hill tail index constitutes the number of existing moments. With the occurrence of many extraordinary profits and losses, which usually appear in connection with volatility clusters, the Hill tail index declines. Hence, a higher Hill tail index indicates a more stable financial market. In the simulations of Section 5, we choose a tail fraction of 5%.

Extraordinary profits and losses are considered especially problematic for financial institutions (BCBS 2006, Brunnermeier 2009). This is obvious, in view of the new formula for determining the regulatory capital for market risk. Herein, we find many terms directly related to them (backtesting exceptions) or periods into which they are incorporated (stressed Value-at-Risk). Before looking at those instruments directly connected to the Basel frameworks, we must first define a model with which they can be analyzed.

3 The model

The financial market model uses a Discrete Choice Approach (DCA), as introduced by Brock/Hommes (1998). The model chosen was suggested by Franke/Westerhoff (2011). They evaluated a number of financial market HAMs with regard to their ability to replicate stylized facts of financial markets, such as volatility clusters, long memory effects and fat tailed return distributions. The model specification chosen here was evaluated most effectively.

A description of the model adjustments can also be found in Hermsen (2011). Here, the differences concerning the financial market stability of the Basel II and III frameworks are elaborated instead of focusing on special instruments and aspects of the Basel III framework, as in this article. The model used is an enhancement of an idea put forward in Hermsen (2010). Here, another heterogeneous model, the Lux/Marchesi model (1999/2000), was employed to explore the effects of the Basel II model. We describe the similarities and differences in the description of the model below.

The price development is given by the log-price of the previous time step p_{t-1} and its change driven by the excess demand

$$p_t = p_{t-1} + \mu(n^f_{t-1} z^f_{t-1} + n^c_{t-1} z^c_{t-1} + n^{reg}_{t-1} z^{reg}_{t-1}). \tag{4}$$

As in the basic model, excess demand is determined by the proportion of chartists and fundamentalists $n^{c,f}_{t-1}$ weighted by their demand $z^{c,f}_{t-1}$. Additionally, we introduce the group of regulated traders. Their weight and excess demand are determined by n^{reg}_{t-1} respectively z^{reg}_{t-1}.

Chartists' and fundamentalists' excess demand is determined by different mechanisms. Chartists buy or sell assets based on the price trend. If the price trend indicates a raising/decreasing market price, they buy/sell. The excess demand is added by a noise term that captures random influences on the chartists' demand

$$z^c_t = \chi(p_t - p_{t-1}) + \sigma^c_t \epsilon^c_t \text{ with } \epsilon^c_t \sim N(0,1). \tag{5}$$

Fundamentalists focus on the fundamental price p^*. If the price is above/below the fundamental price, they expect a downward/upward price correction. As for the chartists, their demand is supplemented by a noise term that captures random influences on their demand:

$$z^f_t = \phi(p^* - p_t) + \sigma^f_t \epsilon^f_t \text{ with } \epsilon^f_t \sim N(0,1). \tag{6}$$

In Formulae (5) and (6), χ and ϕ are strictly positive reaction parameters capturing the intensity at which agents react to the respective trading signal.

The newly introduced group of regulated traders has to be described in more detail. This group of traders is instructed how to trade by regulations. They are not allowed to use the usual chartists' or fundamentalists' rules. Instead they must use a trading rule that is directly dependent on values such as the level of regulatory capital for market risk *lrc* or the BCBS prescribed minimum level of regulatory capital $lrc_{\min}$. To gain a better understanding of the mechanism generating the excess demand of regulated traders, the details of a time series of *lrc* and $lrc_{\min}$ are depicted in Figure 1. The upper panel shows threshold $lrc_{\min}$, which is exceeded between trading days 3300 and 3550.

Figure 1 comes about here

If a financial institution has assets in its portfolio indicating a higher risk than $\mathrm{lrc}_{\min}$, as is the case for the gray shaded area of Figure 1, it has to provide a higher level of regulatory capital. However, the financial institution will try to reduce this additional regulatory capital to a level close to $\mathrm{lrc}_{\min}$ since regulatory capital is expensive compared to loan capital. If a financial institution has high risk positions in its portfolio, it becomes even more expensive to acquire additional regulatory capital. One solution for a financial institution might be to reduce the risk in the portfolio by selling risky assets. This simple consideration leads us to the excess demand generated by regulated traders:

$$
\begin{aligned}
z_t^{reg} &= -\rho \frac{\mathrm{lrc}_{t-1} - \mathrm{lrc}_{\min}}{\mathrm{lrc}_{\min}} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \\
z_t^{reg} &= 0 \text{ if } \mathrm{lrc}_{t-1} < \mathrm{lrc}_{\min}.
\end{aligned}
\tag{7}
$$

This trading rule is constructed in a similar fashion to the fundamentalists' trading rule (cp. Formula (6); recall that p_t is formulated in logarithms.). For both, We use the rate at which a special threshold – p^* for fundamentalists and $lrc_{\min}$ for regulated traders – is exceeded to determine the intensity of the respective group's excess demand. Likewise, ρ can be interpreted in the same way as the constants in Formulae (5) and (6).

If the level of regulatory capital is above the minimum required capital level, regulated traders will try to sell assets to reduce the necessary regulatory capital. As for the fundamentalists, the more considerably the threshold is exceeded, the greater the negative demand. For regulated traders this implies the sale of risky assets. In Figure 1, we recognize an increasing (negative) excess demand of regulated traders z^{reg} (bottom panel) during the period in which $lrc_{\min}$ is exceeded (gray shaded area of the top panel). The highest peak of the time series of the level of regulatory capial *lrc* causes the highest excess demand of regulated traders. Here, more risky assets are sold than at the beginning of this period, when the threshold was exceeded to a lesser extent.

If the minimum capital requirements are higher than the capital requirements, as in the case for the period before time step 3300 and after 3550, $\text{lrc}_{\min}$ is the regulatory capital lrc a financial institution is obligated to hold. Regulated traders can behave according to the trading rules in which they believe; they do not need to care about regulations. Hence, for this case $z_t^{reg} = 0$, as shown in the bottom panel of Figure 1 for the respective time periods.

Unlike than in Hermsen (2010), we use the level of regulatory capital lrc as a reference value for regulated traders directly instead of a backtesting exception. In a nutshell, a backtesting exception occurs if an extraordinary loss occurs on one trading day. However, backtesting exceptions are only one of the values required to determine the level of regulatory capital for market risk.[1] Especially after introducing a new additional risk measure – the stressed Value-at-Risk – into the formula to determine of capital requirements for market risk, which is not directly related to a backtesting exception, it seems to be more reasonable to use lrc to determine z_t^{reg}.

Going back to the formulation of the price change in Formula (4), we have to define the weights of chartists, fundamentalists and regulated traders. Here, we use the same principle as in Hermsen (2010). We first determine the weights of chartists and fundamentalists according to the rules of the basic model of Brock/Hommes and Franke/Westerhoff. We do not need regulated traders to formulate these weights since they do not believe in the rules prescribed by the regulatory authority. Although they have to apply regulations, they believe in chartists' or fundamentalists' rules. Therefore, we add the suffix "bel" to those rules:

$$\begin{aligned} n_t^{f,bel} &= \frac{1}{1+\exp(-\beta a_{t-1})} \\ n_t^{c,bel} &= 1 - n_t^{f,bel}. \end{aligned} \tag{8}$$

where β is the intensity of choice (Brock/Hommes 1998; Franke/Westerhoff 2011). Franke/Westerhoff (2011) define a_t, the attractiveness index, as follows in the HPM

[1] In the next section, a backtesting exception and the calculation method for lrc is defined.

model:

$$a_t = \alpha_n (n_t^{f,bel} - n_t^{c,bel}) + \alpha_0 + \alpha_p (p_t - p^*)^2. \tag{9}$$

Hence, a_t considers the herding behavior of agents[2] (first term), the predisposition of the former strategy (second term) and the misalignment of the price (third term). There are $\alpha_n \geq 0$ and $\alpha_p \geq 0$.

After agents have chosen the trading rules in which they believe, we have to test whether they are affected by regulations and determine the weight of regulated traders. We stated that regulated traders are only active when the level of regulatory capital exceeds the minimum level of regulatory capital ($\mathrm{lrc}_{t-1} > \mathrm{lrc}_{\mathrm{min}}$; cp. Formula (10)). Here, we are faced with the problem of a lack of data on how many traders sell assets according to regulations. We therefore define a maximum fraction of regulated traders $\mathrm{N}^{\mathrm{reg}}$ who behave according to regulations per day[3]. But why do we define it as the maximum fraction?

We assume that the weights of chartists and fundamentalists determine the percentages of $\mathrm{N}^{\mathrm{reg}}$ (if we have 80% fundamentalists and 20% chartists, we also have 80% regulated traders who believe in fundamentalists' rules and 20% regulated traders who believe in chartists' rules). If all agents – chartists and fundamentalists – have to apply regulations, the fraction of regulated traders n_t^{reg} is indeed $\mathrm{N}^{\mathrm{reg}}$. But if, for instance, chartist regulated traders want to sell more assets than prescribed by the regulations ($z_t^c > z_t^{reg}$), they will do so. They are then able to behave according to their conviction and to apply the regulations at the same time. Therefore, they are then chartist traders and not regulated traders. Of course, the same principle is applied if fundamentalist regulated traders wish to sell more assets ($z_t^f > z_t^{reg}$). If both groups want to sell more assets than determined by the z_t^{reg}, the fraction of regulated traders can be even zero, although the $\mathrm{lrc}_{\mathrm{min}}$ is exceeded. These considerations can be summed up in the following formula

[2]Interesting contributions concerning herding behavior in agent-based models can be found in Irle et al. (2011) and Alfarano/Milaković (2009)

[3]In the following simulation study, this fraction $\mathrm{N}^{\mathrm{reg}}$ is varied to obtain reliable results

for determining the weight of regulated traders:

$$
\begin{aligned}
n_t^{reg} &= \mathrm{N}^{\mathrm{reg}} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^c > z_t^{reg} \text{ and } z_t^f > z_t^{reg} \\
n_t^{reg} &= n_t^c \cdot \mathrm{N}^{\mathrm{reg}} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^c > z_t^{reg} \text{ and } z_t^f < z_t^{reg} \\
n_t^{reg} &= n_t^f \cdot \mathrm{N}^{\mathrm{reg}} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f > z_t^{reg} \\
n_t^{reg} &= 0 \text{ if } \mathrm{lrc}_{t-1} < \mathrm{lrc}_{\min} \text{ or} \\
&\quad \text{if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f < z_t^{reg}.
\end{aligned}
\tag{10}
$$

The true weights of the fundamentalists and chartists have to be adjusted by the respective group of regulated traders, applying the same case distinction.

$$
\begin{aligned}
n_t^{f,c} &= n_t^{f,c,bel}(1 - n_t^{reg}) \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^{f,c} > z_t^{reg} \\
n_t^f = n_t^{f,bel}(1 - n_t^{reg});\ n_t^c &= n_t^{c,bel} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^f > z_t^{reg} \text{ and } z_t^c < z_t^{reg} \\
n_t^c = n_t^{c,bel}(1 - n_t^{reg});\ n_t^f &= n_t^{f,bel} \text{ if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^f < z_t^{reg} \text{ and } z_t^c > z_t^{reg} \\
n_t^{f;c} &= 0 \text{ if } \mathrm{lrc}_{t-1} < \mathrm{lrc}_{\min} \text{ or} \\
&\quad \text{if } \mathrm{lrc}_{t-1} > \mathrm{lrc}_{\min} \text{ and } z_t^c < z_t^{reg} \text{ and } z_t^f < z_t^{reg}.
\end{aligned}
\tag{11}
$$

We proceed by explaining the instruments proposed by the BCBS to strengthen the financial institutions' ability to sustain financial crises and incorporate these changes into the model introduced above. We then analyze the effects these instruments have on financial market stability, as defined in Section 2.

4 Instruments introduced by the BCBS and their integration into the model

In this section, we describe the instruments introduced by the BCBS to improve financial market stability, as defined in the previous section. In general, virtually all of the instruments aim to raise the level of regulatory capital. However, we have to differentiate between an increase in the level of regulatory capital for market risk, lrc, and a raise of the the minimum required level of regulatory capital, $\mathrm{lrc}_{\min}$. The first is used to integrate stressed Value-at-Risk; the second is used to introduce the capital conservation and countercyclical buffer. Only the transition period of seven years is not associated with an increase in regulatory capital. Before we explain the instruments in detail, we should bear in mind the structure of the Basel II/III framework.

The overall level of regulatory capital consists of the sum of the level of regulatory capital of the risk types credit, market, and operational risk. Since we explore the effect of regulations on financial markets, we focus mainly on market risk defined as "the risk of change in the value of a financial position due to changes in the value of the underlying components on which that position depends," McNeil et al. (2005, p. 2). Roughly spoken, credit risk considers the risk that a counterparty fails to repay loans to the financial institution. Operational risk captures losses caused by failures of internal processes, employees, or systems of the financial institution or related customers. According to their definition, credit and operational risk influence different areas of the activities of a financial institution to market risk. However, since many of its activities often depend on one another, there are, of course, interdependencies between the three risk groups (Marrison 2002, McNeil et al. 2005).

4.1 Stressed Value-at-Risk (sVaR)

The capital requirements in period t for market risk cr_t of a financial institution are calculated by

$$\mathrm{cr}_t = \max\left(\tfrac{h}{60}\textstyle\sum_{i=1}^{60} \mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t)\right), \tag{12}$$

where $\mathrm{VaR}_{0.99}(\mathbf{10}|t-i)$ is the 99%-VaR of the (cumulative) loss distribution of the next 10 periods (days) and h is a multiplier. Dependent on the result of a backtesting procedure (cp. Annex 10 in BCBS (2006)), the multiplier is chosen from a range between $h = 3$ and $h = 4$ (Stahl 1997). This level of regulatory capital for market risk is increased to a large extent by integrating the stressed Value-at-Risk (sVaR), described in BCBS (2009, 2011b). An additional term is added to Formula (12), which can then be described by

$$\begin{aligned}\mathrm{cr}_t = \max&\left(\tfrac{h}{60}\textstyle\sum_{i=1}^{60} \mathrm{VaR}_{0.99}(\mathbf{10}|t-i), \mathrm{VaR}_{0.99}(\mathbf{10}|t)\right) + \\ \max&\left(\tfrac{h}{60}\textstyle\sum_{i=1}^{60} \mathrm{sVaR}_{0.99}(\mathbf{10}|t-i), \mathrm{sVaR}_{0.99}(\mathbf{10}|t)\right),\end{aligned} \tag{13}$$

where $\mathrm{sVaR}_{0.99}(\mathbf{10}|t-i)$ is the 99%-sVaR of the (cumulative) loss distribution of the next 10 periods (days). The stressed Value-at-Risk is calculated based on a "12-month period of significant financial stress" (BCBS 2009). All other aspects regarding the calculation of the stressed Value-at-Risk remain the same as in the calculation of the Value-at-Risk (BCBS 2009, 2011b). The level of regulatory capital for market risk lrc_t is calculated by dividing cr_t and by portfolio value p. So, we obtain

$$lrc_t = \frac{cr_t}{\exp(p_t)}. \tag{14}$$

The BCBS does not prescribe financial institutions a specific model for calculating of the Value-at-Risk . Hence, we use models commonly used in practice to obtain a quite realistic picture of the practical implications of the instruments introduced in Basel III. The Value-at-Risk is calculated according to Reiss/Thomas (2007) using the return distribution. They define the τ-step VaR at time t, $\mathrm{VaR}_\alpha(\boldsymbol{\tau}|t)$, as required for Formulae (12) and (13) for a portfolio value given at time t with V_t and the quantile of the (cumulative) τ-step return distribution at time t with $Q_\alpha(\boldsymbol{\tau}|t)$ by[4]

$$\mathrm{VaR}_{1-\alpha}(\boldsymbol{\tau}|t) = V_t\left(1 - \exp\left((Q_\alpha(\boldsymbol{\tau}|t)\right)\right). \tag{15}$$

Since we carry out a univariate analysis, we use $V_t = \exp(p_t)$ with p_t calculated using Formula (4). Now we can define a backtesting exception. A backtesting exception occurs if the loss associated with the 1-step-Value-at-Risk at a 99%-level $\mathrm{VaR}_{0.99}(1|t)$ is exceeded. This incident occurs on average 2.5 times a year (1% of 250 trading days). If it happens more frequently, cr_t is additionally increased by a raising factor h in Formulae (12) and (13). The backtesting exception was used in Hermsen (2010) as a threshold for the regulated traders' trading rule of Formula (10). If we look at Formula (13), we can see that the construct of the stressed Value-at-Risk does not correspond directly to the backtesting exception since it is usually simply determined using a completely different time period. Furthermore, since we have to compare the results from Formulae (12) and (13), we require to have a common benchmark. Therefore, it is necessary to directly use the level of regulatory capital as defined in (14).

The risk measure Value-at-Risk is required in both Formulae (12) and (13). Various methods are applied to calculate this risk measure. These models differ with regard to assumptions of the return distribution or the weighting of (recent) historical observations,

[4]The bold $\boldsymbol{\tau}$ in the formula symbolizes the return distribution for the time period from t to τ days. In the case of the Basel II/III framework, the BCBS prescribes $\boldsymbol{\tau} = 10$ days.

for instance. An overview over the models used to calculate the VaR is given in the appendix. Here, we describe how $(Q_\alpha(\boldsymbol{\tau}|t))$ is calculated to obtain the Value-at-Risk using Formula (15).

According to Homburg/Scherpereel (2005), who surveyed German banks concerning the Value-at-Risk models used, the approaches of the appendix are wide-ranging. We assume that each approach is used by one third of regulated traders. Thus, $N^{reg} = \mathrm{N}^{hv} + \mathrm{N}^{hs} + \mathrm{N}^{ew}$ of Formula (10) can be specified in the following manner.

$$\begin{aligned} \mathrm{N}^{hv;hs;ew} &= \frac{1}{3}\mathrm{N}^{\mathrm{reg}} \text{ if } \mathrm{lrc}_{t-1}^{hv;hs;ew} > \mathrm{lrc}_{\mathrm{min}} \\ \mathrm{N}^{hv;hs;ew} &= 0 \text{ if } \mathrm{lrc}_{t-1}^{hv;hs;ew} < \mathrm{lrc}_{\mathrm{min}}. \end{aligned} \tag{16}$$

Hereby, N^{hv} are regulated traders who use historical volatility. N^{hs} and N^{ew} describe the same for historical simulation and the EWMA model, respectively. $\mathrm{lrc}_t^{hv;hs;ew}$ describes the associated level of regulatory capital for market risk calculated by the respective method. In addition to aiming to increase the direct level of regulatory capital for market risk, the BCBS uses an increase in the minimum level of regulatory capital for both the conservation and countercyclical buffer, described in the following subsections.

4.2 The conservation buffer

By introducing a capital conservation buffer, the minimum level of regulatory capital is raised from 8% to rates of 8.625%/9.25%/9.875%/10.5% from 2015 to 2019 (BCBS 2011a; Annex 4). This capital conservation buffer should assure that financial institutions use their common equity to strengthen their capital base instead of paying high dividends and compensation payments in financial crises (BCBS 2011a; 26-28).

The increase in the overall minimum capital requirements has an impact on all risk groups. It is difficult to state which risk group is mainly affected. We can guess that the capital requirement for operational risk may be constant. However, the complexity of Basel III increases, which may increase the probability of (internal) system failures. Credit risk and market risk are doubtlessly affected. Hence, we assume the relative, percentage increase of the overall level of regulatory capital and add this factor to the minimum regulatory capital requirements of all risk types. In our model, this aspect is incorporated by increasing $\mathrm{lrc}_{\mathrm{min}}$ of Formulae (10) and (16) after 250 time steps (one year) in the simulations with the respective factor. Since our model allows a univariate analysis, diversification aspects that blur our results are not considered. We therefore have to assume higher rates of minimum capital requirements (20%, 25%, 30%, 35%, 40%) to deploy our analyses since $\mathrm{lrc}_{\mathrm{min}} = 8\%$ is exceeded at every time step for this reason. We raise the assumed rates of minimum capital requirements by factors of 0.625/8, 0.625/8.625, 0.625/9.25, 0.625/9.875, 0.625/10.5 which is equal to the factors by which the BCBS raises $\mathrm{lrc}_{\mathrm{min}}$. Thus, we gain an impression of the impact an increase in $\mathrm{lrc}_{\mathrm{min}}$ by such a factor has.

In this way, we can mimic the intention associated with this instrument. This is often useful if the real aspect cannot be replicated directly. Direct modeling is not possible due to the complexity of both Basel II and III frameworks. However, we have to find a solution to capture what might happen if the conservation buffer is implemented and, furthermore, the extent to which it influences financial markets compared to the other instruments introduced. It is also important to bear this consideration in mind when integrating the countercyclical buffer into the model.

4.3 The countercyclical buffer

The countercyclical buffer was introduced to build a buffer in periods when the economic situation is sound to ”ensure the banking system has a buffer of capital to protect it against future losses” (BCBS 2011a, 137). The losses during a downturn of the economy are associated with excess credit growth by the BCBS (2010b, 2011a). Furthermore, the BCBS highlights the regulatory capital requirements to meet the macro-financial environment in an adequate manner. Financial markets are an important component of the macro-financial environment and indicate upturns and downturns quite reliably (Westerhoff 2011).

Although the BCBS links upturns and downturns to the increase and decline in system-wide risk measured by credit growth, the associated increase in regulatory capital is not solely added to the level of regulatory capital for credit risk, but to the overall level of regulatory capital. Hence, regulatory capital for market risk is also greatly affected by the countercyclical buffer.

We have to consider the countercyclical buffer in our model, which is dependent on market risk, if we want to test the impact of the Basel III framework on financial markets.

But how should we do this? The BCBS identifies extremely large losses as being especially problematic in periods of downturns (BCBS 2011a, 136). Since downturns of the economy and of financial markets are correlated and the BCBS links the countercyclical buffer to an increase system-wide risk (BCBS 2011a, 137), we have to find an adequate measure. We need an approximation of ”excess aggregate credit growth” – the measure actually used by national authorities to issue or cancel the buffer on a quarterly basis (BCBS 2010b). The BCBS (2010b) and Drehmann et al. (2010) suggest a credit-to-GDP gap to build up a buffer. However, since the variables needed are not included in our financial market model, we have to find an approximation with the variables given in our model, hence, losses due to price decays. Concerning the identification of the transition of good times to bad times in which the buffer should be released, Drehmann et al. (2010) state that two criteria are important: aggregate gross losses at banks and credit contractions in the banking sector. We have to focus on aggregate gross losses at banks. For this measure, Drehmann et al. even link credit and market risk together: ”An ideal measure of aggregate gross losses would capture all sources of losses independent of whether those arise from credit, market, or other risks,” Drehmann et al. (2010, p. 6). However, they argue that such a measure is hard to define.

We have to assume here that aggregate gross losses are connected to losses associated with the portfolio held by the financial institution, hence, a price decay, since we cannot replicate the whole complexity of the Basel III framework with our model. Here, we focus on the impact on our financial market and not on credit risk issues here.

Looking at a typical price and return time series presented in the top part of Figures 2 and 3, we recognize that increasing market risk, represented by an increasing volatility of returns and Value-at-Risk, occurs together with extraordinary losses (cp. the large volatility clusters at time steps 2000 and 3500 in Figures 2 and 3). For simplification reasons, we set the threshold of an extraordinary loss to a loss of 2% on one day. If this loss is realized more than twice in one quarter, we assume a period of stress for financial institutions, in which system-wide risk increases such that the countercyclical buffer is canceled by the regulatory authority. In periods when such an extremely large loss does not occur that frequently, additional capital requirements, such as the countercyclical buffer, are demanded by the national regulatory authority, to be prepared for times of crisis.

The bottom-left panels of Figures 2 and 3 reveal that the countercyclical buffer is indeed canceled during crashes and additional regulatory capital is held during calm periods with financial market stability. It seems to be a good approximation to model the impact of the countercyclical buffer on financial market stability.

Just as we implemented the capital conservation buffer with lrc_{min} (cp. Formulae (10) and (16)) into our model, we raise lrc_{min} if we observe a maximum of two extremely large losses quarterly as defined above. In the other case, if more than two extremely large losses are observed, lrc_{min} is not raised. This procedure is visualized using the dotted line in the bottom-left panels of Figures 2 and 3.

The "stairs" from time steps 5500 to 6500 in lrc_{min} represent the transition period in which the stepwise integration of the conservation buffer is implemented. The transition period is described in the next subsection.

4.4 The transition period

During the transition period from 2013 to 2019, minimum regulatory capital requirements are raised stepwise from 8% to 10.5%. Here, in the first phase until 2015, the quality of the regulatory capital is increased. Thereafter, the quantity of regulatory capital is also increased stepwise by implementing the capital conservation buffer (BCBS 2010a).

This stepwise increase may also have an effect on financial market stability, since the minimum capital requirements are adjusted, regardless of whether there are times of high volatility or downturns of the economy in these periods. Slovik/Cournede (2011) also consider the transition period to be a critical period. However, they investigated the influence for macroeconomic variables and not for financial market stability. It is therefore important to analyze the impact of this stepwise rise over a period of five years. The stepwise increase is easy to implement in the model. We simply have to adjust lrc_{min} (cp. Formulae (10) and (16)) at the specified time steps for this purpose. This procedure is in line with integrating capital conservation and the countercyclical buffer into the model.

In the next section, we analyze whether or not the instruments described lead to a stabilization of the financial market according to the stability measures introduced. For this purpose, we first describe the characteristics of one typical time series, as shown in Figures 2 and 3, and then highlight the results of a Monte Carlo simulation with 100 of those time series in Section 4. The structure of this section follows that of the previous section.

5 Simulation results

The time series depicted in Figures 2 and 3 contain 10000 observations. The first 1500 observations (six years) were neglected in the calculation of the initial values for the risk measures ((stressed) Value-at-Risk), the capital requirements and the level of regulatory capital. The time series for varying proportions of regulated traders are simulated with the same random variables for the noise terms. This enables us to obtain the pure effect caused by adding or excluding the respective instrument, because the other settings and parameters remain constant. Concerning the other constants and parameters, we use the same setting as in Franke/Westerhoff (2011)[5]. For the additional parameter ρ of the regulated traders' trading rule in Formula (10), we use the same value as for the reaction parameter of fundamentalists ϕ. Hence, we set $\rho = \phi$. The reason for this is the simultaneous modeling of both trading rules, as described in Section 3.

Three time periods are highlighted in Figures 2 and 3. The first and third shaded areas show the end of periods for which the minimum level of regulatory capital is constant. The first area represents the basic setting of the minimum level of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$. The third shaded area shows $\mathrm{lrc}_{\mathrm{min}}$ raised by 35%. We choose the end of those time periods to consider stable dynamics of the model not influenced by initial settings or the transition period, which is represented by the second shaded area in the figures. As the transition period is a five-year period (1250 observations), the first and third shaded areas contain the same number of observations, enabling the three time periods to be compared one another.

The upper panels represent the price development, whereas the bottom two panels of the upper part of both figures show the return time series. The upper return time series displays the situation for an unregulated time series (basic) and the bottom one for a situation where maximum 4% of the regulated traders ($\mathrm{N}^{\mathrm{reg}}$) are affected by regulations. The bottom part of both figures shows the time series for the level of regulatory capital for market risk lrc and the minimum level of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$ for each of the used VaR approaches used by the financial institutions.

We require both figures to analyze the effects of the instruments. In Figure 2, all time series are computed using incorporated stressed Value-at-Risk to calculate capital

[5]These values are $p^* = 0, \phi = 0.12, \chi = 1.5, \alpha_0 = -0.336, \alpha_n = 1.839, \alpha_p = 19.671, \sigma^f = 0.708, \sigma^c = 2.147$ and the reaction parameter of the regulated traders $\rho = 0.12$.

requirements cr (Formula (13)). In Figure 3, we use the former regulation with Formula (12) to calculate cr. The findings concerning the stressed Value-at-Risk are described in Sections 5.1.

The impact of the capital conservation buffer (Section 5.2) is investigated by comparing shaded areas 1 and 3 with one another. We can therefore conclude which effects the increase in the regulatory capital has.

The countercyclical buffer (Section 5.3) is added to the left-hand panels of Figures 2 and 3. This effect is "switched off" in the right-hand panels . The existence of this effect can be identified by the different time series of the minimum level of regulatory capital in the bottom part of the figures.

For the consequences resulting from the transition period (Section 4.4), we require the shaded area 2. We can compare this time period with shaded areas 1 and 3 for which the minimum level of regulatory capital was quite constant for hundreds of time steps.

For the time series depicted, we can state an obviously reduced number of volatility clusters for using stressed Value-at-Risk and a reduced volatility in shaded area 3 compared to areas 1 and 2. Another aspect is the similarity of the direct counterparts in the left- and right-hand panels, which may be evidence of a low impact of the countercyclical buffer in both Figures 2 and 3.

The mechanism causing the changes in the model are analyzed in Hermsen (2011). In short, the overall excess demand does not change considerably if we incorporate regulated traders. A small reduction of d occurs compared to the basic model only for time series with the stressed Value-at-Risk . However, the fluctuation of the excess demand in the respective groups is more significant. For higher N^{reg} fundamentalists become more dominant than chartists. This keeps the price closer to its fundamentals. However, the absolute excess demand of chartists also increases, which may heighten the risk of crashes. The intensity of the changes in excess demand, and which of these effects is dominant is decisive for the influence on the stability measures[6].

However, we have to explore more than one time series to obtain reliable results for our presumptions. For this purpose, we simulate 100 time series for different proportions of regulated traders in a Monte Carlo simulation. The results, presented in Figures 4 to 7,

[6]However, for (unrealistic) large N^{reg}, the sales of regulated traders become dominating, leading to very large crashes. This case is discussed in Hermsen (2011). In this article, we set N^{reg} to a range in which the dynamics remain stable.

will be explained in the description of the impact of the instruments introduced.

5.1 Stressed Value-at-Risk

From left to right, the results for time periods 1 to 3 are presented in Figure 4. This means that the left-hand panels show the results for the basic minimum level of regulatory capital lrc_{min}, the middle panels the transition period for which lrc_{min} is increased stepwise, and the right-hand panels present a situation for which lrc_{min} was raised to the new level after a time period of 3000 time steps, which complies with about 12 years (the time periods are visualized in Figures 2 and 3 with the shaded areas). There are three parts in Figure 4 separated by horizontal lines.

From top to bottom, the results are given for each of the stability measures volatility, distortion, and the Hill tail index. The top lines of each part show the results calculated using the stressed Value-at-Risk implemented, hence, cr and lrc are calculated using Formula (13). In the bottom lines of each part, we use Formula (12) without stressed Value-at-Risk to calculate these values.

The boxplots can be interpreted as follow: the left- and right-hand borders of the box represent the 25% and 75% percentile of the 100 time series concerning volatility, distortion and the Hill tail index. The vertical line in the box is the median of the stability measures' values and the point is the mean of the 100*1250=125,000 observations of each shaded area (cp. Figures 2 and 2). The horizontal line shows the range of the stability measures' values. From bottom to top, the boxplots visualize the 100 time series for maximum proportions of 0% to 5% regulated traders.

The analysis indicates a stabilization of the financial market following the introduction of the stressed Value-at-Risk[7]. Comparing the upper lines with sVaR of each of the parts of Figure 4 with the bottom parts without sVaR, we identify a clear stabilization achieved following the implementation of this instrument. Looking at volatility in the upper part, we see a clear decline in volatility with increasing N^{reg} for each time period. This effect is even more significant for distortion in the middle part. In the bottom part, the value for the Hill index increases for each time period, indicating less extreme profits and losses. All stability measures point to a stabilization of the financial market following

[7] According to BCBS (2011c), different methods can be used to calculate Value-at-Risk and stressed Value-at-Risk. In the paper, we always use the same method to calculate both. Since the results do not differ considerably regarding stressed Value-at-Risk, this assumption does not affect the results significantly.

the integration of stressed Value-at-Risk.[8]

How the dynamics of the model is affected by the stressed Value-at-Risk is described in great detail in Hermsen (2011) [9]. To describe the intuition behind this, the introduction of the stressed Value-at-Risk leads more frequently to a regulation of the financial market and to a higher excess demand of fundamentalists, which drives the price back to its fundamental value. The stressed Value-at-Risk raises the level of regulatory capital more frequently over the minimum level of regulatory capital (although it was raised by capital conservation and countercyclical buffer), which enforces the use of regulations. We have to differentiate between two cases to sketch the mechanism – one if the price is above the fundamental value and the other if the price is below it.

If the price is above the fundamental value, regulations usually become increasingly important in times of large positive returns. The reason for this is that these returns cause increasing risk, measured by the Value-at-Risk, and, hence, an increasing level of regulatory capital (cp. Formula (14)). Additionally, regulations cause negative excess demand in the market and the large positive returns decline compared to a situation without regulations. The trading signal of chartists declines, causing a decline in the group of chartists. The reduced amplitude of positive returns and faster reversion to the fundamental value due to the larger excess demand of fundamentalists and regulated traders reduces volatility and, especially, distortion. Extraordinarily large losses are reduced by the negative excess demand of regulated traders.

If the price is below the fundamental value, a greater number of larger negative returns cause regulations to be applied more intensively. Large negative returns have the same effect regarding Value-at-Risk and the level of regulatory capital as large positive returns. Regulations enforce the price decay. This strengthens the group of fundamentalists who believe in a reversion to the fundamental value. The weight of chartists, which declines anyway if the price falls, becomes even smaller compared to an unregulated financial market. The higher fraction of fundamentalists drives the price back to the fundamental value in small steps, damped by regulated traders, which reduces distortion and volatility and heightens the Hill tail index.

[8] We present the results without implementing a countercyclical buffer. However, very similar results can be observed with implemented countercyclical buffer.

[9] Here is additionally explained which dangers a too high fraction of regulated traders have. A too strong regulation can cause severe crashes.

5.2 The conservation buffer

The effect of the conservation buffer is analyzed in Figure 5 and Table 1. We first look at Figure 5, where we find boxplots for all three time periods (cp. shaded areas of Figure 2). The boxplots are presented for a situation in which the stressed Value-at-Risk is implemented (but without a countercyclical buffer, which is discussed in the next section), since we know its stabilizing effect from Section 4.1. The left-hand panels show a situation with maximum 2% fraction of regulated traders, the right panels with a maximum $\mathrm{N}^{\mathrm{reg}} = 5\%$.

Figure 5 comes about here

We compare time periods 1 (bottom boxplot) and 3 (top boxplot) because for time period 3 the relative increase in the basic level of regulatory capital is conducted as described in Section 4.2 (time period 2 in the figure will be considered in the following Section 4.4). For volatility (top panels), we cannot see a strong change for the low fraction of regulated traders in the market. For the higher fraction, however, volatility increases if the conservation buffer is implemented. For the other two stability measures, we recognize more stable results if the conservation buffer is excluded for both fractions: the distortion is lower and the Hill tail index higher for time period 1. But are these effects significant? Do these results hold if we change the basic level of regulatory capital chosen with $lrc_{\mathrm{min}} = 0.3$ to this point in the article, as in Figures 2 and 3?

For this purpose, we have to analyze Table 1. For each of the proportions of regulated traders, there is a p-value for a T-Test given[10]. In the top part of the table, the basic level of regulatory capital is given by 0.2 (we can picture this by reducing $\mathrm{lrc}_{\mathrm{min}}$ to 0.2 in the bottom parts of Figures 2 and 3). In the middle part, we present the level previously used in the analysis with $\mathrm{lrc}_{\mathrm{min}} = 0.3$. In the bottom part (on the next page), $\mathrm{lrc}_{\mathrm{min}}$ is raised to 0.4. In the second (stressed Value-at-Risk (sVaR)) and third column (countercyclical buffer (cb)), we see which instruments are included or excluded.

[10]We test whether the mean value μ of the respective stability measure indicates a more stable value in period 1 (p1) compared to period 3 (p3) for the 100 time series of the Monte Carlo simulation. For this purpose, we test hypothesis $H_0 : \mu_{\mathrm{p1}} \geq \mu_{\mathrm{p3}}$ against $H_1 : \mu_{\mathrm{p1}} < \mu_{\mathrm{p3}} \iff \mu_{\mathrm{diff}} = \mu_{\mathrm{p3}} - \mu_{\mathrm{p1}} > 0$ with $(\widehat{\mu}_{\mathrm{diff}} - \mu_{\mathrm{diff}})/\widehat{\sigma}_{\mathrm{pooled;diff}}) \cdot \sqrt{T_1 + T_2 - 2} \overset{as.}{\sim} \mathcal{N}(0,1)$ since $T_1 = T_2 = 100$. The p-value for this test is given in Table 1. Since a stabilized financial market is associated with $\mu_{\mathrm{p1}} > \mu_{\mathrm{p3}}$ for the Hill tail index, we test $H_0 : \mu_{\mathrm{p1}} \leq \mu_{\mathrm{p3}}$ against $H_1 : \mu_{\mathrm{p1}} > \mu_{\mathrm{p3}}$ for this stability measure.

Table 1 comes about here

Concerning volatility, the values are not significant for lower fractions of regulated traders. For higher values, we obtain significant values for included sVaR, but only for lower basic lrc_{min} levels (cp. top two lines of the top and middle part of Table 1).

Distortion increases with the conservation buffer, independent of the use of the countercyclical buffer, even with proportions of 2% of regulated traders. For lower levels of lrc_{min} of 0.2 and 0.3, this also holds if sVaR is included.

The *p*-values of the Hill tail index are often not significant. This indicates a minor influence of the countercyclical buffer on the occurrence of extreme profits and losses. There are some exceptions, however. For high N^{reg} when sVar is included and cb excluded, the Hill tail index even indicates an increase in extraordinary profits and losses for all lrc_{min} levels.

Summing up this subsection, introducing the conservation buffer does not have such a strong influence on financial market stability as the stressed Value-at-Risk. In contrast to the first instrument explored, however, especially for distortion, it has a significant destabilizing effect. It is virtually impossible to reduce volatility and the presence of extraordinary profits and losses by using this instrument. For higher N^{reg} when sVaR is implemented, the stability measures of volatility and the Hill tail index even indicate a destabilization for the conservation buffer. It could be that the temporary increase in additional minimum capital requirements, as suggested by the BCBS with the countercyclical buffer, has a stabilizing effect.

The reason for the slight increase in distortion is that the positive effect of the higher level of regulatory capital on the model dynamics caused by the stressed Value-at-Risk is reduced. As described at the end of the previous subsection, a higher level of regulatory capital stabilizes the financial market with additional negative excess demand when sharp price changes occur. A higher minimum level of regulatory capital reduces the gap between lrc and lrc_{min} and disposes of some of the stabilizing excess demand of regulated traders. This additionally dampens the greater influence of fundamentalists, hamping the rapid reversion to the fundamental value. Therefore, distortion increases slightly.

5.3 The countercyclical buffer

This aspect is analyzed in Figures 6 and 7. Figure 6 consists of three parts: as usual, the top part stands for volatility, the middle part for distortion, and the bottom part for the Hill tail index. In each part, the top panels visualize a situation with sVaR and the bottom panels a situation without sVaR for constant $N^{reg} = 4\%$. The results for time periods 1 and 3 are presented in the left- and right-hand panels, respectively. In each panel, there are two boxplots for each basic level of regulatory capital $lrc_{min} \in \{0.2, 0.25, 0.3, 0.35, 0.4\}$ (cp. the ordinates of Figure 6 which are denoted by "basic lrc_{min}"). The top and bottom boxplots show a situation with and without a countercyclical buffer (cb). A statistically significant higher value for the time series without cb is indicated by the light ($0.9 < \widehat{p} < 0.99$) and dark-gray ($\widehat{p} > 0.99$) colors of the boxplots[11].

Figure 6 comes about here.

The first finding is that the countercyclical buffer has virtually no effect on financial market stability if the sVaR is excluded. The bottom panels of each part indicate no significant difference concerning the top and bottom boxplot.

However, the result is different if sVaR is implemented, as in the top panels of each part. Independent of the lrc_{min} level for each stability measure, we obtain a destabilizing effect of the countercyclical buffer. The mean, median, and quartiles of all the top boxplots with implemented cb are right-hand compared to the bottom panels without cb for volatility and distortion. Many of the differences for volatility and most of them for distortion are statistically significant. This can be interpreted as an increase in volatility and distortion with cb. For the Hill tail index, the statistics mentioned visualized by the boxplots are left-hand. Especially for time period 3, we obtain statistically significant differences. This indicates more extraordinary profits and losses with the cb. Are these results significant and valid for other N^{reg}? This topic is highlighted in Figure 7.

Figure 7 comes about here

[11] We use a very similar test to test in the previous section. We now define $\mu_{\text{diff}} = \mu_{\text{no cb}} - \mu_{\text{cb}} > 0$ with $\mu_{\text{(no) cb}}$ as the mean of the 100 time series with(out) a countercyclical buffer.

The figure is structured somewhat differently to the previous figure (because we also need it in the next section to the analyses of the transition period). The left- and right-hand panels are for situations with a maximum proportion of 2% and 5% regulated traders, respectively, for a situation with $\mathrm{lrc}_{\mathrm{min}} = 0.3$ (in the previous Figure 6 we did not see any strong effect concerning the difference between included or excluded cb caused by variation of the $\mathrm{lrc}_{\mathrm{min}}$ level. Hence, we can keep it constant). For each time period, we have – as in the previous figure for each $\mathrm{lrc}_{\mathrm{min}}$ level – the top boxplot where cb is implemented and the bottom where it is not implemented. The significance levels are also marked as in the previous figure.

For lower proportions of regulated traders, we do not identify any statistically significant difference, as the left panels indicate. However, for higher proportions of regulated traders we have significant results, especially for volatility and distortion. The occurrence of extraordinary profits and losses is only weakly affected by the countercyclical buffer. Given that this was one of the main reasons for introducing the countercyclical buffer, it seems to have failed its purpose. The increase in volatility shown in both Figures 6 and 7 is also a problematic result. The pure increase in the minimum levels of regulatory capital $\mathrm{lrc}_{\mathrm{min}}$ do not seem to be an applicable instrument to increase financial market stability. This result is yielded by both the analysis of capital conservation and the countercyclical buffer. Concerning the model dynamics, the slight increase in distortion for the countercyclical buffer can be explained in the same way as described previously for the capital conservation buffer.

5.4 The transition period

The transition period is characterized by stepwise increased levels of minimum capital requirements $\mathrm{lrc}_{\mathrm{min}}$ (cp. the shaded area for time period 2 in Figures 2 and 3). The effect of this instrument can be examined by Figures 4, 5 and 7 from Sections 5.1, 5.2 and 5.3.

Looking first at the middle panels (from left to right) of Figure 4, we are unable to identify any strong differences in the results compared to periods 1 and 3. The boxplots have a similar position concerning mean, median, quartiles, and range. The stepwise transition to the new capital requirements does not seem to have a significant influence on volatility, distortion or extraordinary profits and losses. This can be ascertained by Figures 5 and 7 for other proportions of regulated traders. We do not obtain significantly different results compared to time periods 1 and 3 for neither a proportion of 2% or 5% of regulated traders. However, the characteristics of the boxplots are sometimes more similar to period 1. If there are significant differences between period 1 and 3, the mean for the time series of the respective stability measure is between the respective values for the other two time periods (as for volatility and the Hill tail index for $N^{reg} = 5\%$ in Figure 7).

These results show that the results described in Sections 4.1 and 4.3 can be adapted to the transition period. In the next subsection we summarize and interpret the results of this section.

5.5 Discussion of the impact of the instruments

Before we discuss the results, it is important to summarize the essential differences concerning the three instruments introduced by the BCBS to stabilize financial markets. The first, the stressed Value-at-Risk, is an instrument especially formulated for market risk. It affects only the level of regulated capital for market risk lrc. In other words, the regulatory capital associated with this special risk type concerning a portfolio held by the financial institution, for instance, is changed.

The other two instruments – conservation and countercyclical buffer – are simultaneously aimed at all risk types. For these, the capital requirements relating to a special asset or portfolio are not raised. Both instruments increase the overall minimum level for regulatory capital lrc_{min} for all risk types credit, market, and operational risk at a special rate. The financial institution may decide to which risk types these changes are assigned. We assume that the minimum level for regulatory capital used for market risk is raised by the rate at which the overall minimum level of regulatory capital is raised.

The result is that the stressed Value-at-Risk has the deepest impact on financial market stability. Concerning all stability measures – volatility, distortion, and Hill tail index – we identify a stabilizing influence. The impact of conservation and countercyclical buffer is lower. Furthermore, neither create the desired effect intended by the BCBS to stabilize financial markets. For higher fractions, even a significant destabilization can be measured. A pure increase in the minimum capital requirements – permanently, as for the conservation buffer, or temporarily, as for the countercyclical buffer – are not effective for reducing bubbles and crashes. The most stable period analyzed is period 1 without conservation and countercyclical buffer, but with the implementation of stressed Value-at-Risk.

Hence, the main finding of the simulation study is that direct regulations influencing the calculation of regulatory capital connected to a special risk be associated with a financial institutions' assets, such as the introduction of the stressed Value-at-Risk, seems to be an effective way to enhance financial market stability. The relatively imprecise common increase of minimum capital requirements for all risk types have proven to be not very effective, sometimes even creating contrary effects for both the conservation and the countercyclical buffer.

6 Conclusion

In a heterogeneous agent model by Franke/Westerhoff based on Brock/Hommes' Discrete Choice Approach, we integrated mechanisms to test the instruments proposed by the Basel Committee on Banking Supervision (BCBS). We explored their effect on financial market stability, measured by volatility, distortion, and the Hill tail index. The new instruments which are mainly relevant for market risk are the stressed Value-at-Risk, the capital conservation buffer, the countercyclical buffer and the long transition period of seven years in which the instruments are adopted stepwise.

The stressed Value-at-Risk is the only instrument that can be solely connected to market risk and which directly increases the level of regulatory capital associated with assets held by a financial institution. The effect is a clear stabilization, indicated by a decline in volatility, distortion and an occurrence of extraordinary profits and losses. The two instruments which have to be deployed to all risk types of the Basel III framework – conservation and the countercyclical buffer – raise the minimum capital requirements regardless of the risk situation. They do not have a stabilizing effect. In turn, they create greater distortion. Sometimes both may destabilize the financial market for high fractions of regulated traders in the market, also concerning volatility and the Hill tail index and hence, extraordinary losses. However, the strongest impact on financial market stability is caused by the stressed Value-at-Risk. Its quite positive influence is slightly weakened by the other two instruments. All instruments implemented together led to a stabilized financial market. The transition period does not affect the above-mentioned findings.

Challenges for further research may focus on the different risk types. First, it might be interesting if the observed larger effect resulting from raising the level of regulatory capital associated with the assets held by a financial institution compared to an increase in the minimal capital requirements can also be observed for credit risk. For credit risk, which is also calculated using the risk measure Value-at-Risk, a kind of stressed Value-at-Risk can be added to the calculation formula, as proposed for market risk. Here, the regulation authority may define a special credit risk portfolio consisting to a certain extent of toxic assets so that financial institutions are also well-prepared for periods of stress concerning credit risk. This might be more effective than raising minimum capital requirements.

In addition, since the risk groups credit, market and operational risk add up to the overall level of regulatory capital it would be interesting to have a model comprising them all. That way, the financial institution may also lower or raise credit risk to react on changes in market risk and vice versa. To reach this target, we do not only need time series for shares, but also for credit derivatives, governments bonds and mortgage loans. For many assets belonging to credit risk, it will even be difficult to calculate a present value.

Here, it might be necessary to take preliminary steps before obtaining a large model that is able to shed light on the (dangers of) the interconnectedness of the different risk types and their influence on financial markets, as well as the real economy. In view of the actual financial crises in that these issues are inweaved into a structure which is very hard to comprehend and control, such a model would be useful. Concerning the interconnectedness and influence of regulations on financial markets, this article might be a first step in this direction.

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Appendix: Value-at-Risk models

Historical volatility approach (hv)

The first approach can be directly deviated from the Basel II framework (BCBS 2006, 2009, 718 (LXXVI) (c) and (f)); Danielsson et al. 1998), since it suggests the square root of time rule. The basic model to calculate returns y_i is formulated as

$$y_i = \mu + u_i. \tag{17}$$

An assumption of the very simple historical volatility approach is $u_i = \sigma\epsilon_i$ with $\epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1)$. As a consequence of the normal distribution for the α-quantile it follows, due to the additivity property, that

$$Q_\alpha(\boldsymbol{\tau}|t) = \tau\mu + z_\alpha\sqrt{\tau}\sigma. \tag{18}$$

We then need the result of Formula (18) to be able to calculate the Value-at-Risk with Formula (15).

Historical simulation (hs)

Applying the historical simulation, we arrange the returns in descending order. The α-quantile of $y_{(n)}, y_{(n-1)}, \ldots, y_{(n\ (1-\alpha))}, \ldots, y_{(1)}$ where $y_{(n)} \leq \ldots \leq y_{(1)}$, which we use to determine $\mathrm{VaR}_\alpha(1|t)$, is the smallest value $y_{(n\ (1-\alpha))}$ not exceeding $n\ (1-\alpha)$, so that

$$Q_\alpha(1|t) = y_{(n\ (1-\alpha))}. \tag{19}$$

To calculate the τ-step VaR, a bootstrap approach with $\tau \cdot 5000$ observations is used. The $\mathrm{VaR}_\alpha(\boldsymbol{\tau}|t)$ can be determined from the 5000 cumulated ten-step returns in an analogous manner to that in (19). The Value-at-Risk is calculated using (15).

Exponential weighted moving average (EWMA) approach (ew)

The exponential weighted moving average model (EWMA) following Zangari (1996) is also often used by financial institutions (Holton 2003). The weight placed on the most recent observation is higher, and declines for prior observations. In the basic model

$$y_i = \mu + u_i \text{ with } u_i = \sigma_i \epsilon_i \text{ and } \epsilon_i \overset{i.i.d.}{\sim} \mathcal{N}(0,1),\ i = 1, \ldots, t-1, t, \tag{20}$$

the conditional volatility at time t is modeled by

$$E[u_{i+1}^2|t] = E[(y_{i+1} - \mu)^2|t] = h_t \text{ with } \widehat{h}_{1|t} = (1-\lambda)u_t^2 + \lambda \widehat{h}_t. \tag{21}$$

We assume $u_i \sim \mathcal{N}(0, \sigma^2)$ for the estimation of the one-step VaR. If we replace σ^2 with $\widehat{h}_{1|t}$ and assume that $\mu = 0$, we obtain

$$\widehat{y}_{1|t} \sim \mathcal{N}(0, \widehat{h}_{1|t}) \text{ and } \frac{\widehat{y}_{1|t}}{\sqrt{\widehat{h}_{1|t}}} \sim \mathcal{N}(0,1),$$

respectively, and further $Q_\alpha(1|t) = z_\alpha \sqrt{\widehat{h}_{1|t}}$.

Since $\widehat{h}_{1|t}$ is the best estimation for $u_{t+\tau}$, it follows

$$Q_\alpha(\boldsymbol{\tau}|t) = z_\alpha \sqrt{\tau \widehat{h}_{1|t}}.$$

Basic level of regulatory capital = 0.2								
Stability			p-value of the difference test					
measure	sVaR	cb	0%	1%	2%	3%	4%	5%
Volatility	x	x	0.0934	0.4873	0.7356	0.9472*	0.9595*	0.8484
	x		0.0934	0.5817	0.8252	0.9827*	0.9830*	0.9691*
		x	0.0934	0.2351	0.2136	0.3388	0.1123	0.1021
			0.0934	0.2264	0.2461	0.2897	0.1715	0.2453
Distortion	x	x	0.7720	0.8250	0.9198*	0.9674*	0.9840*	0.9885*
	x		0.7720	0.8838	0.9935*	0.9975**	0.9990**	0.9999**
		x	0.7720	0.8583	0.9144*	0.9069*	0.9301*	0.9787*
			0.7720	0.8701	0.9263*	0.9374*	0.9714*	0.9842*
Hill tail index	x	x	0.4565	0.8825	0.5158	0.7676	0.9837*	0.9106*
	x		0.4565	0.8575	0.5400	0.9946**	0.9852*	0.9640*
		x	0.4565	0.4439	0.4216	0.3287	0.4937	0.5265
			0.4565	0.4906	0.4393	0.4255	0.4553	0.5363

Basic level of regulatory capital = 0.3								
Stability			p-value of the difference test					
measure	sVaR	cb	0%	1%	2%	3%	4%	5%
Volatility	x	x	0.0934	0.2627	0.5922	0.5652	0.8861	0.9311*
	x		0.0934	0.4182	0.5439	0.7552	0.9838*	0.9816*
		x	0.0934	0.1317	0.1802	0.2317	0.2053	0.1995
			0.0934	0.1353	0.2236	0.2430	0.2067	0.2388
Distortion	x	x	0.7720	0.8311	0.8758	0.9554*	0.9821*	0.9850*
	x		0.7720	0.7354	0.8076	0.9768*	0.9913**	0.9931**
		x	0.7720	0.8621	0.9109*	0.9240*	0.9367*	0.9508*
			0.7720	0.8657	0.9171*	0.9303*	0.9429*	0.9593*
Hill tail index	x	x	0.4565	0.5038	0.7574	0.5422	0.4424	0.8505
	x		0.4565	0.7080	0.7080	0.3610	0.8960	0.9944**
		x	0.4565	0.4740	0.4818	0.4768	0.6171	0.6603
			0.4565	0.4361	0.4749	0.5256	0.6178	0.6589

to be continued on the next page

Basic level of regulatory capital = 0.4

Stability measure	sVaR	cb	p-value of the difference test 0%	1%	2%	3%	4%	5%
Volatility	x	x	0.0934	0.3276	0.5293	0.6185	0.6016	0.8023
	x		0.0934	0.3220	0.4779	0.4092	0.5646	0.8986
		x	0.0934	0.0741	0.0884	0.0919	0.0962	0.1011
			0.0934	0.0842	0.0893	0.0935	0.0996	0.1075
Distortion	x	x	0.7720	0.8881	0.9083*	0.9690*	0.9931**	0.9998**
	x		0.7720	0.8736	0.9499*	0.9873*	0.9994**	0.9981**
		x	0.7720	0.7885	0.8073	0.8151	0.8193	0.8232
			0.7720	0.8034	0.8114	0.8197	0.8244	0.8288
Hill tail index	x	x	0.4565	0.5192	0.5575	0.7018	0.8965	0.7885
	x		0.4565	0.3915	0.8741	0.8077	0.6444	0.9433*
		x	0.4565	0.4840	0.4224	0.4063	0.3754	0.3581
			0.4565	0.4621	0.4256	0.3745	0.3458	0.3628

*: significant with $0.9 < p$-value<0.99; ** significant with p-value>0.99

Table 1: Results of the Monte Carlo simulation for the conservation buffer

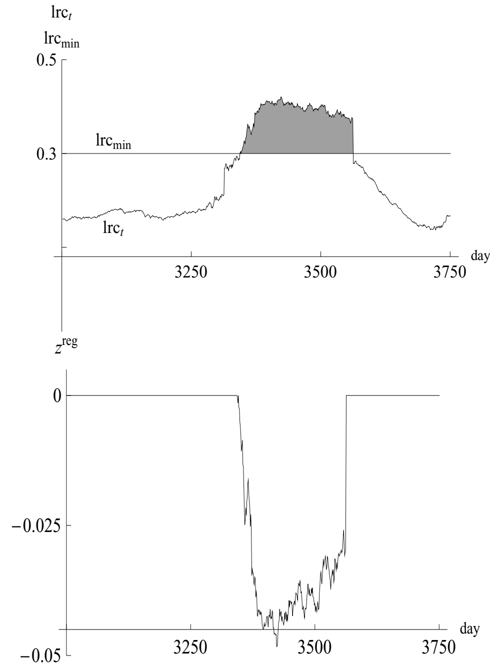

Figure 1: Generation of the excess demand of regulated traders z^{reg}

Top panel: Detail of the time series of the level of regulatory capital (lrc_t) and the minimum level of regulatory capital (lrc_{min}).

Bottom panel: Detail of the time series of regulated traders' excess demand (z_{reg}) resulting from lrc_{min} and lrc_t from the top panel.

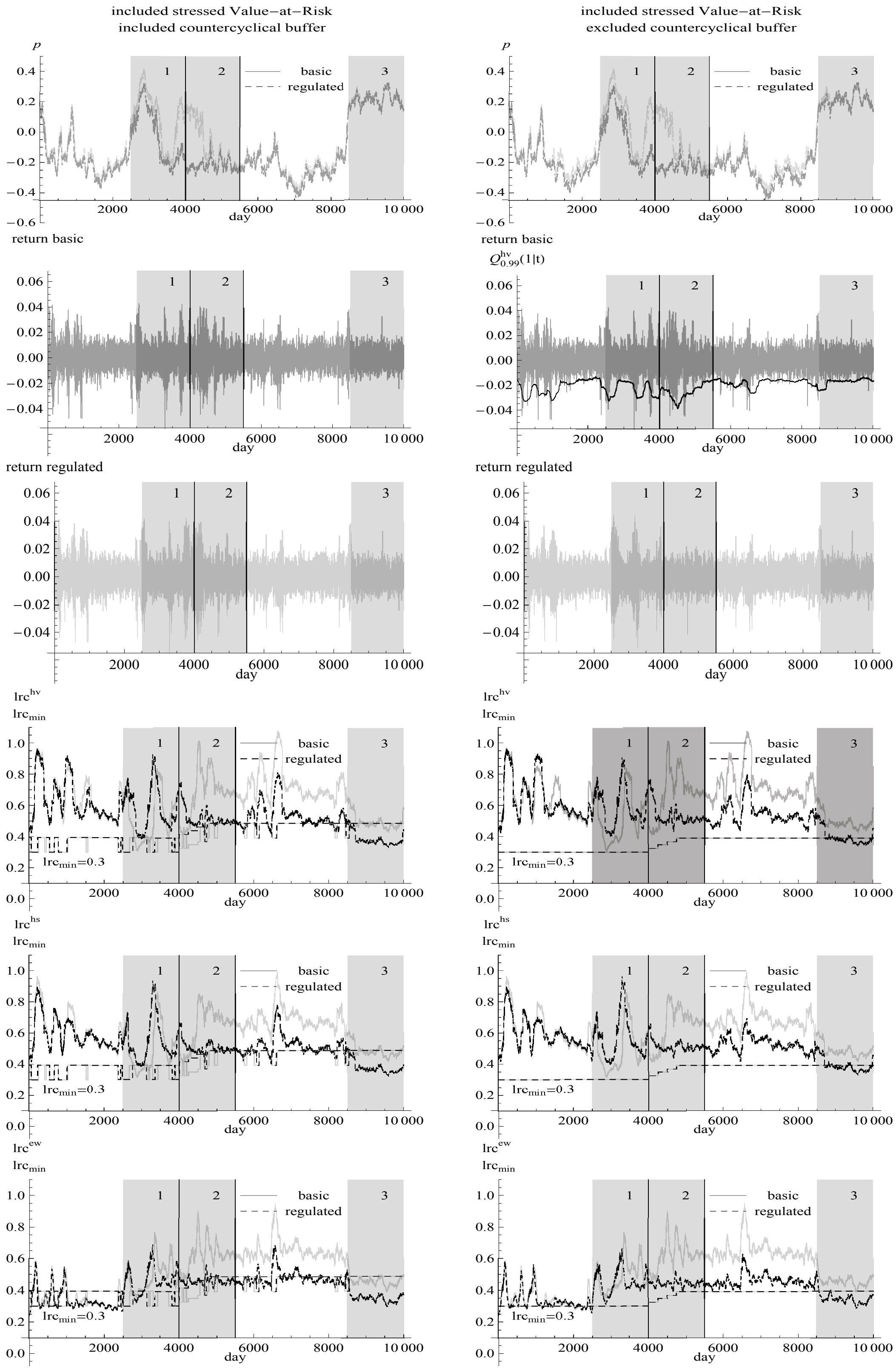

Figure 2: Analysis of regulations with the use of stressed Value-at-Risk

Left-hand panels with the countercyclical buffer: from top to bottom the panels present the time series of the price, the return time series without regulations, the return time series for $N^{reg} = 4\%$ and the (minimum) level of regulatory capital for the VaR approaches – historical volatility (hv), historical simulation (hs) and EWMA (ew).
Right-hand panels: these panels are interpreted in the same way as the left-hand panels, albeit without the countercyclical buffer.

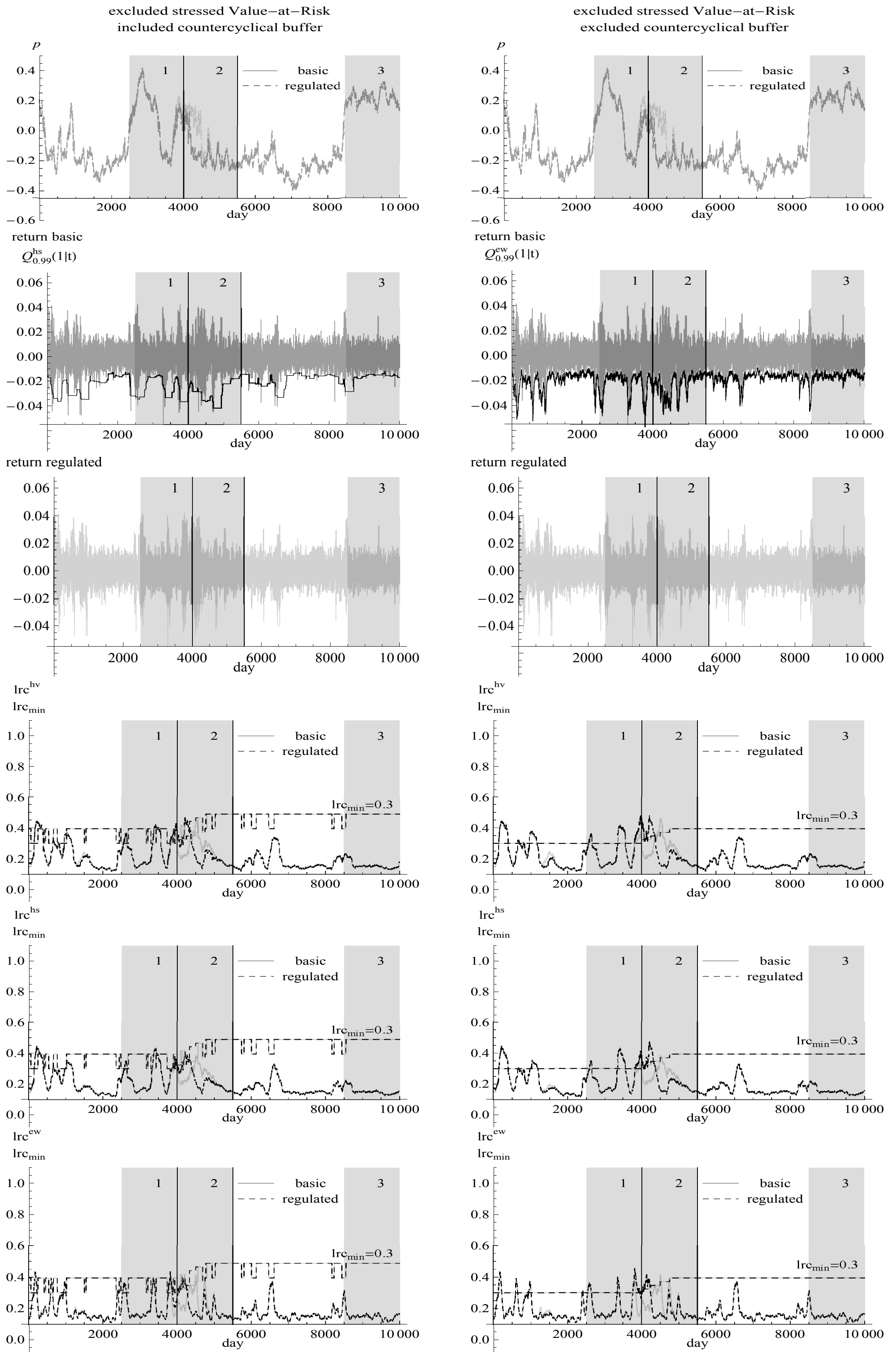

Figure 3: Analysis of regulations without the use of stressed Value-at-Risk

Left-hand panels with the countercyclical buffer: from top to bottom the panels present the time series of the price, the return time series without regulations, the return time series for $N^{reg} = 4\%$ and the (minimum) level of regulatory capital for the VaR approaches – historical volatility (hv), historical simulation (hs) and EWMA (EW).

Right-hand panels: these panels are interpreted in the same way as the left-hand panels, albeit without the countercyclical buffer.

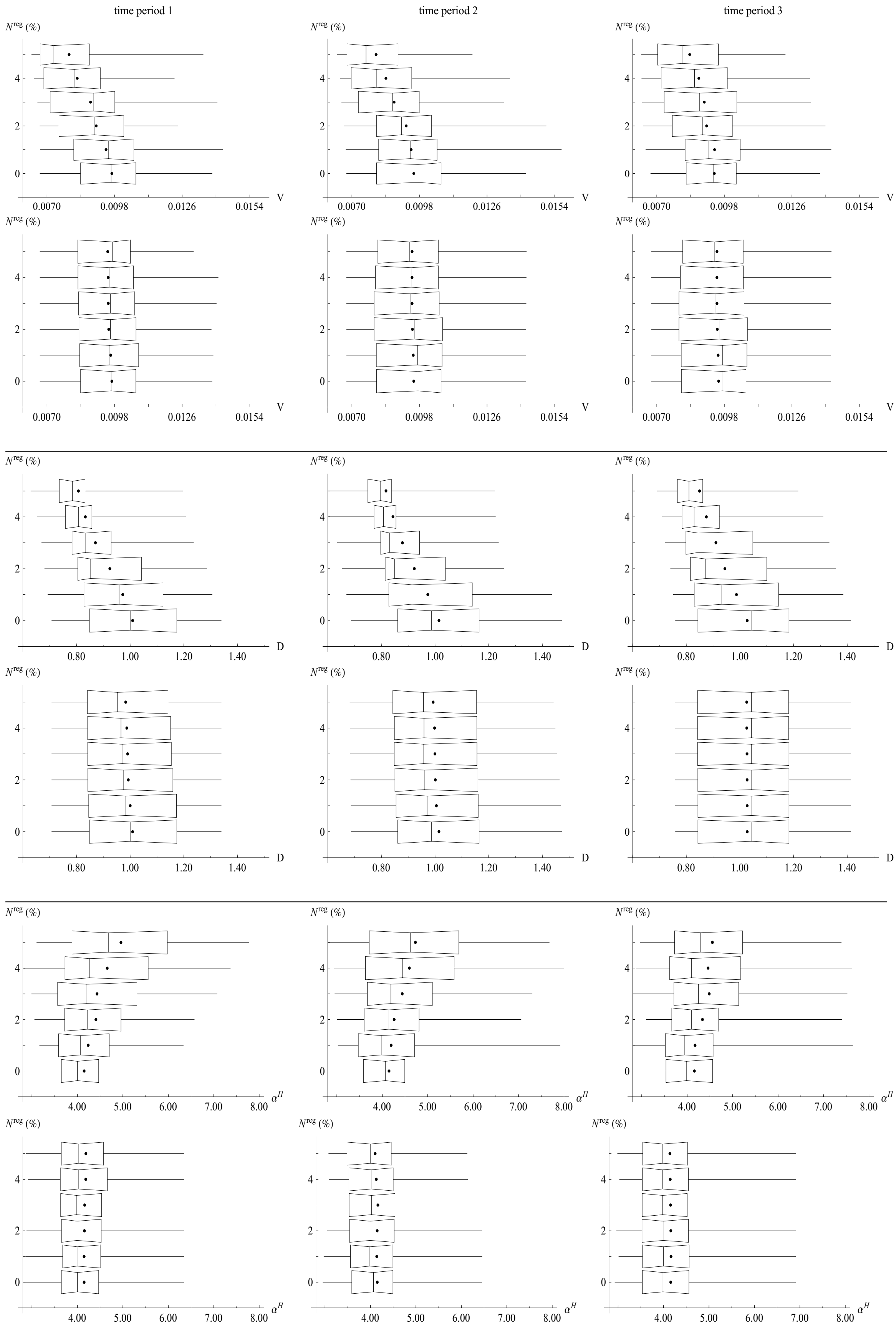

Figure 4: Analysis of financial market stability influenced by the stressed Value-at-Risk
Top part: from left to right, the panels present the boxplots for the time series of the Monte Carlo simulation for volatility with increasing minimum level of regulatory capital in time periods 1 to 3 for implemented (top line) and non-implemented (bottom line) stressed VaR. The countercyclical buffer is not considered.
Middle part: these panels are interpreted in the same way as the top panels, albeit for distortion.
Bottom part: these panels are interpreted in the same way as the top panels, albeit for the Hill tail index.

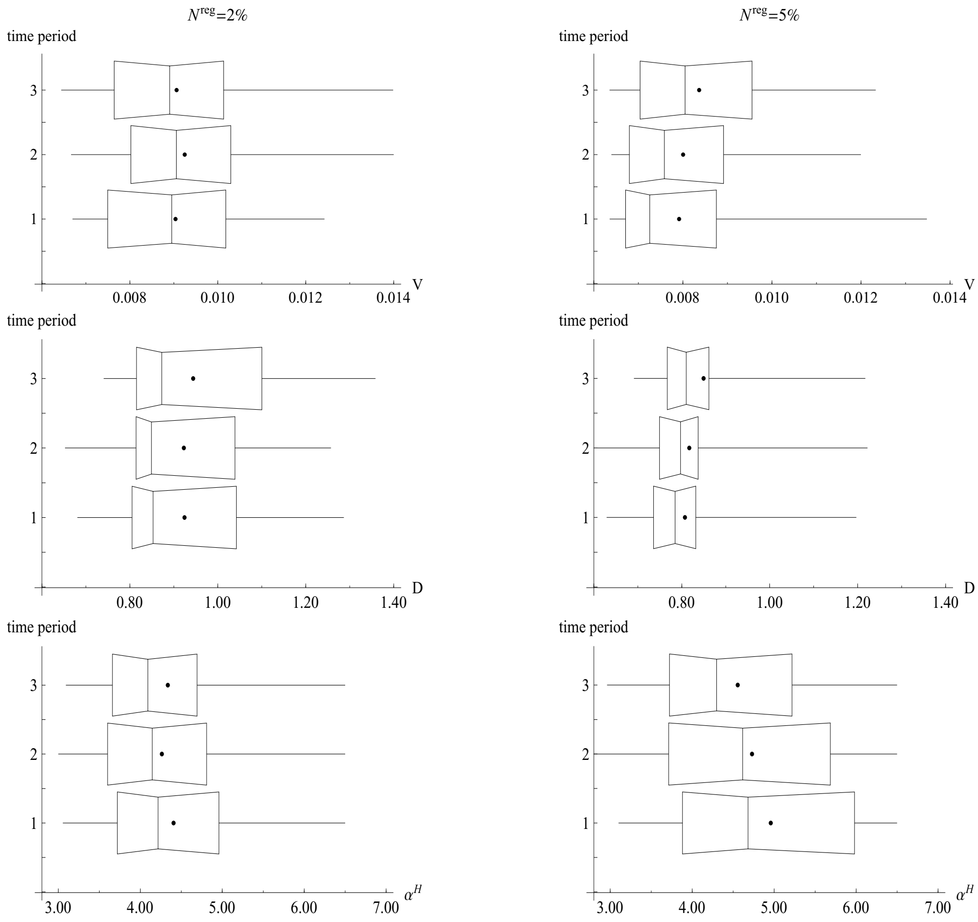

Figure 5: Analysis of financial market stability influenced by the conservation buffer
Top panels: from left to right the panels present boxplots for the time series of the Monte Carlo simulation for volatility with a fraction of $N^{reg} = 2\%$ and 5%. The stressed Value-at-Risk is considered, but the countercyclical buffer is not. The basic level of regulatory capital is 0.3.
Middle panels: these panels are interpreted in the same way as the top panels, albeit for distortion.
Bottom panels: these panels are interpreted in the same way as the top panels, albeit for the Hill tail index.

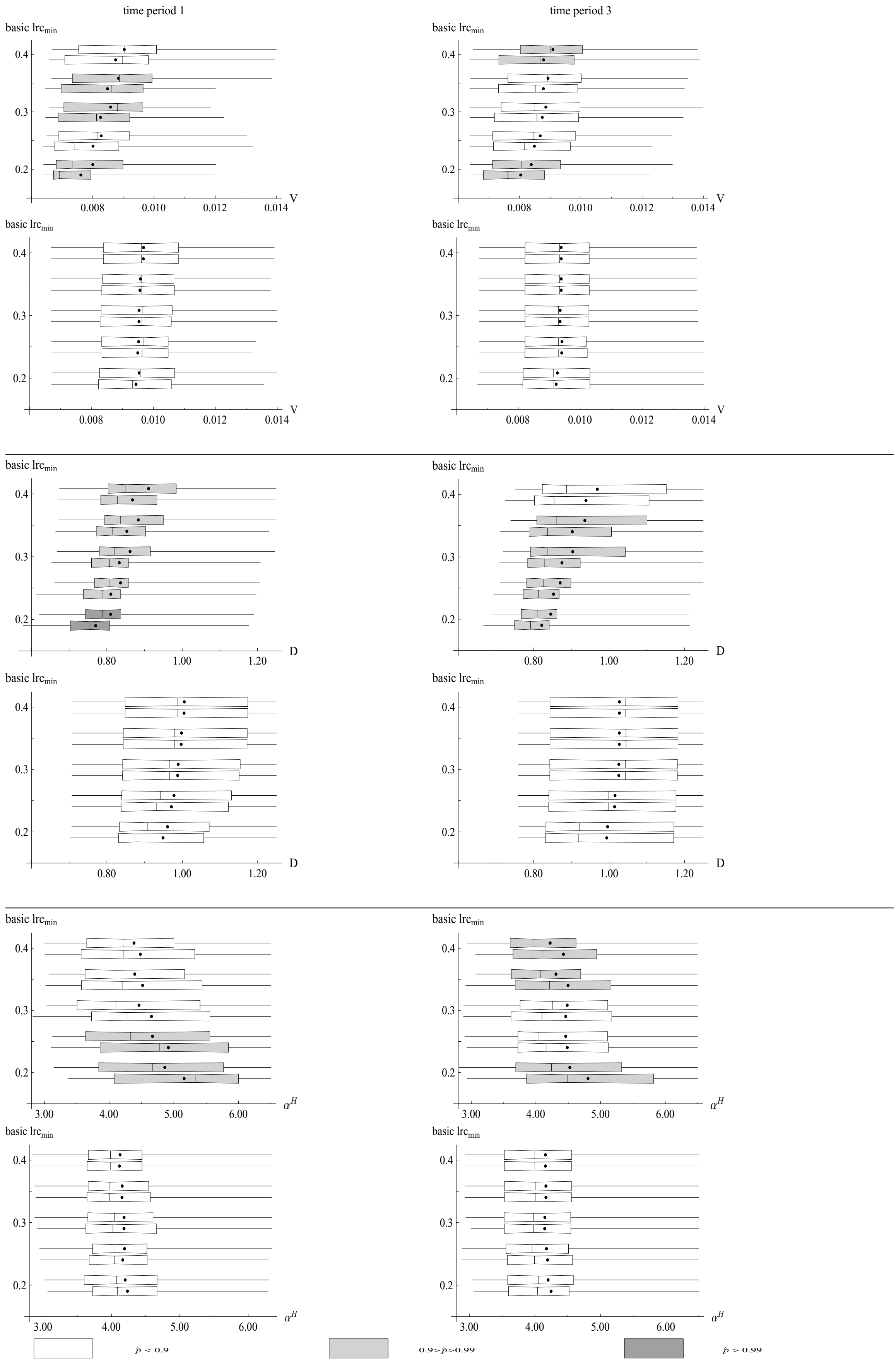

Figure 6: Analysis of financial market stability influenced by the countercyclical buffer
Top part: from left to right, the panels present boxplots for the time series of the Monte Carlo simulation for volatility for time periods 1 and 3. The basic level of regulatory capital ($\mathrm{lrc}_{\mathrm{min}}$) is varied. The countercyclical buffer is not considered in the top boxplots and considered in the bottom boxplots for each $\mathrm{lrc}_{\mathrm{min}}$ level. In the top/bottom line, the stressed Value-at-Risk is included/excluded.
Middle part: these panels are interpreted in the same way as the top panels, albeit for distortion.
Bottom part: these panels are interpreted in the same way as the top panels, albeit for the Hill tail index.

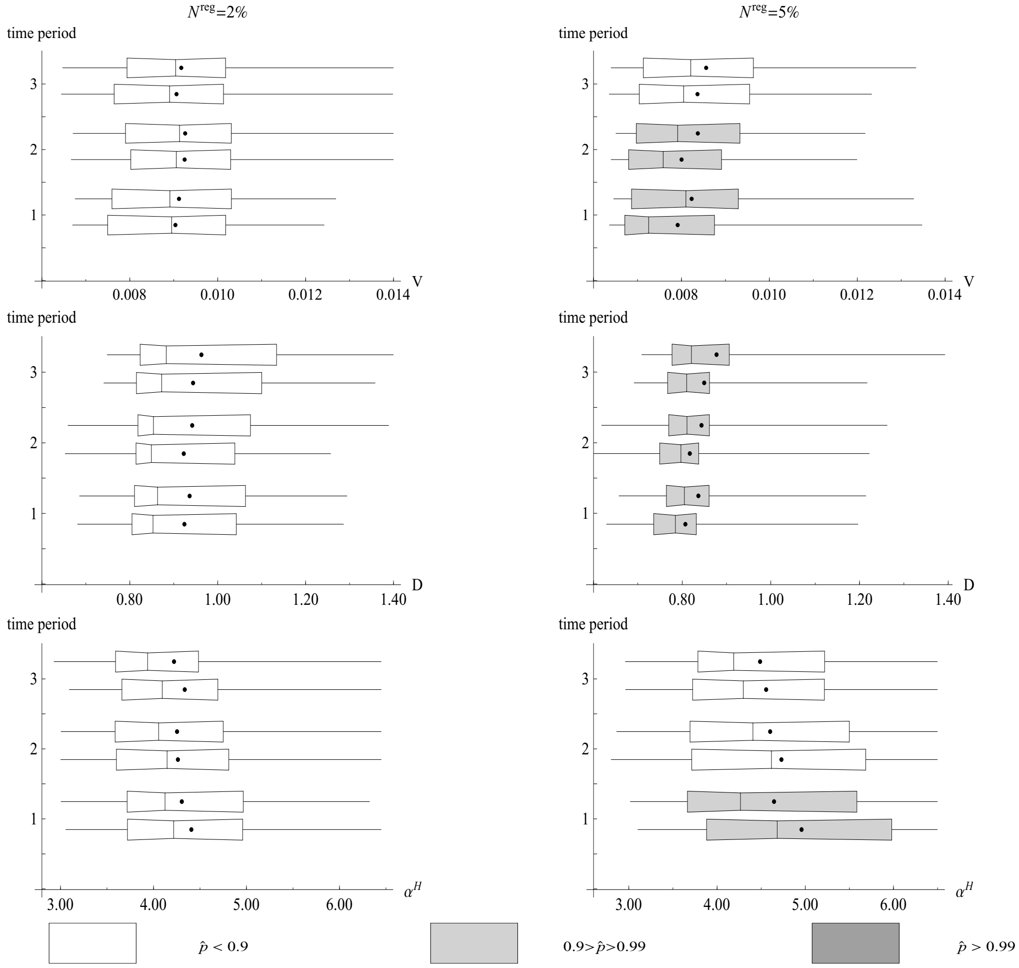

Figure 7: Analysis of the effect of the countercyclical buffer with the stressed VaR implemented

Top panels: from left to right the panels present the boxplots for the time series of the Monte Carlo simulation for the volatility, distortion and the Hill tail index for a maximum proportion of 2% of regulated traders for a situation with (bottom boxplot for each time period) and without (top boxplot of each time period) a countercyclical buffer.
Bottom panels: these panels are interpreted in the same way as the top panels, albeit with a maximum proportion of 5% of regulated traders.