Impact Assessments of the CAR Regulation using Artificial Markets

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Abstract. In this study, we assessed the impact of capital adequacy ratio (CAR) regulation like that in the Basel regulatory framework. To asses impact such as destabilizing effects (e.g., whether CAR regulation destabilizes markets or not), we conducted simulations of an artificial market, one of the computer simulations imitating real financial markets. And, we proposed a new model with continuous double auction markets, stylized trading agents and two kinds of portfolio agent. The portfolio agents had trading strategies incorporating Markowitz's portfolio optimization. Additionally, the portfolio agents of one type were under regulation. From the simulations, we found that: 1. adopting portfolio optimization as each agent's strategy stabilizes markets; 2. the existence of CAR regulation destabilizes markets; 3. CAR regulation can cause significant price shocks; 4. CAR regulation also can suppress price increases; 5. CAR regulation pushes down market prices. From these results, we conclude that CAR regulation can have negative effects on asset markets.

Keywords: Artificial market · CAR regulation · Portfolio.

1 Introduction

In December 2017, the Basel Committee on Banking Supervision reached an agreement on a reformed international regulatory framework for banks [2]. This agreement set out changes to "Basel III", one in a series of banking regulations beginning with "Basel I" in 1988, aimed at avoiding serious financial incidents fraught with so-called "systemic risk."

Systemic risk is one of the most significant dangers to financial markets, wherein small triggers cause huge financial shocks because of economic system failures. For example, the financial crisis of 2007-2008 was triggered only by a crisis in the subprime mortgage market in United States. It affected not only US financial markets, but also financial markets around the globe, including those of Japan. Such systemic risks can seriously destabilize markets, and the current Basel regulatory framework is designed with the intention of reducing them.

Regarding the history of these frameworks, a modified Basel I was agreed to in 1996 [3]. This regulatory framework included market operation risks for the first time. The Capital Adequacy Ratio (CAR) regulation was established after Basel II, and modifications to it have subsequently been made [1]. This regulation aims to prevent banks from going bankrupt as a result of financial shocks and obligates them to keep enough money on hand. It calls on banks to do risk management when they hold risky assets such as equities, derivatives, and so on. However, when markets fluctuate remarkably, the risk of assets increases and the risk management prevents banks from retaining such assets. Thus, banks have to sell their assets, and markets destabilize as a result.

Although CAR regulation was introduced as a way of reducing systemic risks, the possibility of it actually having a destabilizing effect on markets was suggested by Benink et al. [5]. According to that study, the CAR regulation of the Basel II accord destabilizes markets when they have uncertainties.

Hermsen studied the destabilizing effect by conducting simulations [9]. Although his research showed that Basel II has a destabilizing effect on markets, it only tested its assertions with a single asset, which is far from the reality of large markets.

Another study by Yonenoh [13] tested the destabilizing effect with multi-asset simulations. However, the model used in it contained a number of unrealistic assumptions. For example, the model's markets did not have enough buy or sell orders. In addition, under the CAR regulation, agents could not obtain the global optimized position, which means that under the regulation, agents got lost in the diversity of assets, and using an unrealistic optimization algorithm, they would buy or sell only one or two kinds of asset. Moreover, although the trading strategy of the agents considered changes occurring over different time spans, such as a day or month, the markets themselves or the changes in price in his model did not reflect what occurs in real markets.

Thus, as a way of overcoming the shortcomings of the previous studies, we decided to make a new model incorporating multi-asset markets and CAR regulation.

In the new model, we used artificial market simulations, one of the multi-agent simulations. Simulations of this type are widely used (for example, see Torii et al.'s work [11]), and they have a number of benefits. For instance, when a new regulation is about to be introduced, it can be tested in simulations to determine if it will cause any harm to real markets. In addition, comparative experiments can be conducted using simulations.

In particular, we chose Plham (Platform for Large-scale and High-frequency Artificial Market) [12] for the artificial market simulations, on which we examined the destabilizing effects of CAR regulation and made the new multi-asset model. Moreover, we sought to reveal other effects of CAR regulation through these simulations.

2 Model

Here, we describe the new multi-asset model of the artificial market. The model contains markets and agents of different types, acting like traders in real financial markets and using their own strategies. The types of agent are as follows.

- Stylized trading agents
- Non-regulated portfolio agents
- Regulated portfolio Agents

Each agent can buy or sell any asset in the markets subject to restrictions such as cash, leverage, or CAR regulation (Fig. 1). The markets are based on Torii et al.'s multi-asset artificial market [11]. The stylized trading agents are based on Chiarella and Iori's model [6].

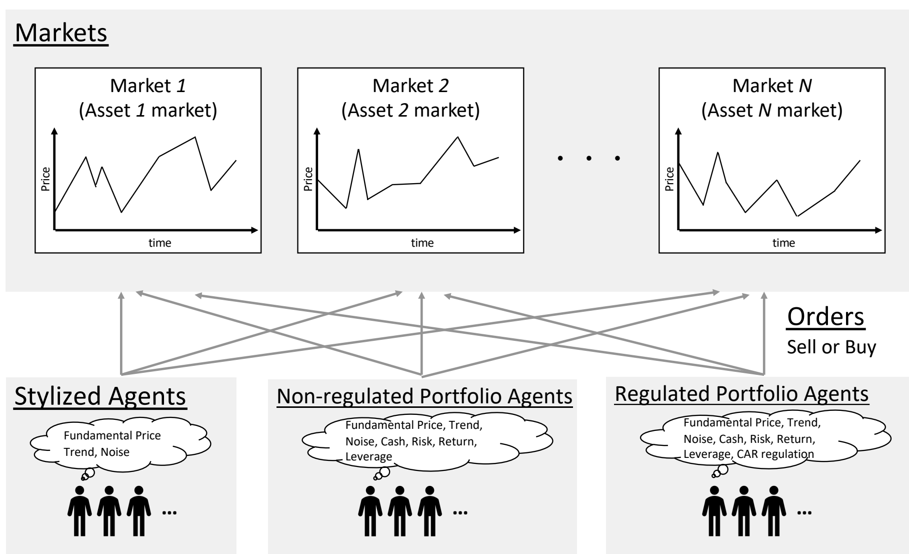

Fig. 1: Model outline. The model consists of a number of markets in which three types of agent trade assets.

In every step of the simulation, some agents are chosen and place their orders. The number of those agents is the same number as the number of markets. Thus, it is not fixed how many orders are placed or how many orders are contracted in one step.

2.1 Markets

Every asset has a unique market with a continuous double auction mechanism for setting the market price. Any sell or buy order can be placed and the prices

Sell Order Book Price	Sell Order Book Amount	Buy Order Book Price	Buy Order Book Amount
400.5	50	400.499	40
400.528	38	400.387	28
400.69	20	400.2	5
401.2	1	400.19	20
401.321	2	400.0	3
401.555	30	399.9	10
402.001	4	399.857	2

(a) Before inputting a new order

Sell Order Book Price	Sell Order Book Amount	Buy Order Book Price	Buy Order Book Amount
400.5	50	400.53	80 <- NEW
400.528	38	400.499	40
400.69	20	400.387	28
401.2	1	400.2	5
401.321	2	400.19	20
401.555	30	400.0	3
402.001	4	399.9	10

(b) Inputting 80 buy orders at 400.53

Sell Order Book Price	Sell Order Book Amount	Buy Order Book Price	Buy Order Book Amount
400.5	50	400.53	80 <- NEW
400.528	38	400.499	40
400.69	20	400.387	28
401.2	1	400.2	5
401.321	2	400.19	20
401.555	30	400.0	3
402.001	4	399.9	10

(c) Contracting 50 orders at 400.5 and 30 orders at 400.528

Sell Order Book Price	Sell Order Book Amount	Buy Order Book Price	Buy Order Book Amount
400.528	8	400.499	40
400.69	20	400.387	28
401.2	1	400.2	5
401.321	2	400.19	20
401.555	30	400.0	3
402.001	4	399.9	10
402.02	12	399.857	2

(d) After contracting

Fig. 2: Continuous double auction mechanism for setting the market price.

of orders are the real number (not limited to integers). Examples of order books are shown in Fig. 2. Before inputting a new order, usually, there are also other orders on both sell and buy order books. (Fig. 2 (a)) Then, if one agent input 80 buy orders at 400.53, the orders are placed on a buy order book. (Fig. 2 (b)) In the case of the order books that appear in Fig. 2, the 80 new buy orders can be contracted with existing sell orders, 50 sell orders at the price of 400.5 and 30 orders in 38 sell orders at the price of 400.528. (Fig. 2 (c)) After contracting, only 8 sell orders in 38 sell orders at the price of 400.528 are still on the sell book, and all contracted orders vanish. (Fig. 2 (d))

Market prices are decided separately for every asset in each market through the continuous double auction mechanism. Transaction fees are ignored.

Every asset has a fundamental price. This price is for agents to decide their own estimated value for each asset, and it is determined in accordance with multivariate geometric Brownian motion (known as a random walk). In the simulations, the mean of the Brownian motion was set at 400.0, and the variance was set at 1.0×10^{-6}.

In addition, we assumed that there was no correlation between any pairs of assets.

2.2 Agents

The three types of agent roughly imitate traders in real markets. Each one has its own trading strategy or trading algorithm, which is explained below. Initially, all agents have 50 assets per market.

2.3 Agents: Stylized Trading Agents

The stylized trading agents are based on those of Chiarella and Iori [6].

In every step, the stylized trading agents estimate their reasonable price for each asset by using historical data and fundamental prices. They use three types of index, which they calculate by themselves using their own unique parameters.

- F: Fundamentalist component (Estimation based on the fundamental prices)
- C: Chartist component (Trends)
- N: Noise

A stylized trading agent, agent i, decides its reasonable price for asset (market) s at time t, as follows.

Agent i has three unique weights; $w_F^i \geq 0$ for F, $w_C^i \geq 0$ for C, and $w_N^i \geq 0$ for N (where $w_F + w_C + w_N > 0$). The estimated geometric return $r_t^{i,s}$ is

$$r_t^{i,s} = \frac{1}{w_F^i + w_C^i + w_N^i}(w_F^i F_t^{i,s} + w_C^i C_t^{i,s} + w_N^i N_t^{i,s}). \tag{1}$$

As described below, w_F, w_C, and w_N were set to exponential distributions with means of 10.0, 1.0, and 10.0. $F_t^{i,s}$, $C_t^{i,s}$, and $N_t^{i,s}$ are defined with p_t^s (the price at time t), p_t^{*s} (the fundamental price at time t), τ_r (mean reversion time, which indicates how long the agent assumes it takes for the price to go back to the fundamental price), τ (the agent's time horizon, which means how far back into the past the historical data goes that the agent uses), and $N(0, \sigma_N^i)$ (a normal (Gaussian) distribution). In the simulations, τ_r was a uniform distribution $[50, 150]$, τ was a uniform distribution $[100, 200]$, and $\sigma_N^i = 1.0 \times 10^{-3}$.

$$F_t^{i,s} = \frac{1}{\tau_r^i} \ln\left(\frac{p_t^s}{p_t^{*s}}\right) \tag{2}$$

$$C_t^{i,s} = \frac{1}{\tau} \sum_{j=1}^{\tau} \ln\left(\frac{p_{t-j}^s}{p_{t-j-1}^s}\right) \tag{3}$$

$$N_t^{i,s} \sim N(0, \sigma_N^i) \tag{4}$$

On the basis of the equations above, the agent decides its reasonable price $p_{t+\Delta t}^{i,s}$ at time $t + \Delta t$:

$$p_{t+\Delta t}^{i,s} = p_t^s \exp\left(r_t^{i,s} \Delta t\right). \tag{5}$$

Then, on the basis of this price, the agent decides whether to buy or sell one unit share; if $p_{t+\Delta t}^{i,s} > p_t^s$, the agent buys one unit of asset s, and if not, the agent sells one unit of asset s at time t.

Stylized trading agents are aimed at making enough orders for contracting. This is because, if there were few orders on the markets' order books, an agent's order would not be contracted when other portfolio agents make orders. Thus, only stylized trading agents are allowed to "sell short", which is to place sell orders without holding stock, and "margin trade", which is to place orders without holding enough money.

In addition, stylized trading agents can access and buy or sell any asset in the markets, and they make decisions separately whether they will buy or sell each asset.

2.4 Agents: Non-Regulated Portfolio Agents

Non-regulated portfolio agents have a trading strategy based on portfolio optimization. This type of agent is based on Yonenoh's multi-asset agents with risk management [13].

In the same way as stylized trading agents, non-regulated portfolio agents can access all markets and can buy or sell any asset. However, in contrast to stylized trading agents, non-regulated portfolio agents choose their position, how many shares of each asset they will buy or sell, inclusively. That is, whether they will buy or sell an asset depends on the other assets, and the decision also depends on the results of the portfolio optimization.

Non-regulated portfolio agents optimize their position in each τ_p^i step. τ_p^i is the term in which to keep the current position. This variable is given at random to each agent, following an exponential distribution whose mean and standard deviation are each 150. Thus, the agents take actions only in each τ_p^i step. The actions are as follows.

1. Cancel orders which have not been contracted yet.
2. Calculate reasonable values of every asset in the same way as stylized trading agents.
3. Revise the portfolio with the portfolio optimization algorithm described below.
4. On the basis of the revised portfolio, make orders for the difference with those of the current portfolio.

Markowitz's mean-variance approach [10] is used in the optimization phase (the third phase above). The expected utility function is defined with a position matrix $\mathbb{x}$, matrix of reasonable values P_{rsn}, and variance-covariance matrix of every asset for the last τ steps Ω. ${}^tA$ means the transposed matrix of A.

$$\mathrm{EU}(\mathbb{x}) = {}^tP_{rsn}\mathbb{x} - \frac{1}{2}{}^t\mathbb{x}\Omega\mathbb{x} \tag{6}$$

The constraints are as follows. The agents have a budget, and they are not allowed to sell short. Thus, all components in $\mathbb{x}$ are nonnegative. Agents find $\mathbb{x}$ that fits the constraints and maximizes $\mathrm{EU}(\mathbb{x})$.

Non-regulated portfolio agents have capital and leverage. In the simulations, the capital was 6,000 per market and the leverage limit was 10, which means that the budget limit is 60,000 per market. For example, if there are five markets, the budget limit is 300,000.

2.5 Agents: Regulated Portfolio Agents

Regulated portfolio agents are almost the same as non-regulated portfolio agents. However, they have additional constraints, which model the CAR regulation. The CAR regulation is based on Basel I [3] and Basel II [1].

The CAR regulation in this model uses the Value at Risk (VaR) and regulates agents when the value of assets held by each agent falls.

$$(\text{CAR}) = \frac{(\text{Capital})}{12.5 \times (\text{Markets Risk})} \geq 8\% \tag{7}$$

This equation follows the rule modeling Basel I after introduction of market risk regulation [3]. The equation above is also defined by it.

Markets risk is calculated as

$$(\text{Markets Risk}) = (\text{Current Total Share Price}) \times (1 - \exp(\text{VaR})). \tag{8}$$

The current total share price does not include cash, because cash is meant to be a non-risk property. According to this equation, the more leverage agents take on, the more risk they have to take on as well. The "$(1 - \exp(\text{VaR}))$" part indicates the possibility of deficits using VaR. Because VaR is calculated on a logarithmic scale, it is included as an exponent in this equation.

VaR is calculated as

$$(\text{VaR}) = -1.0 \times (99\% \text{ One-sided Confidence Interval}) \times \sqrt{T} \times \sqrt{\mathbb{x}\Omega\mathbb{x}}. \tag{9}$$

This calculation involves taking the floor of the upper one-sided confidence interval and uses the root T multiply method [8]. $\mathbb{x}$ is the position matrix of all assets. The holding term of an asset T is set to 10 steps, and Ω is the variance-covariance matrix of all assets for the last 250 steps, as described in Basel I and II [4], whose CAR regulation uses historical data for 250 business days and expects a holding term of 10 business days.

When the agents' portfolio violates the regulation, they revise their portfolios as follows.

1. Calculate CAR based on the current position $\mathbb{x}$ (referred to as CAR($\mathbb{x}$)).
2. Calculate R.
$$R = \frac{0.08}{\text{CAR}(\mathbb{x})} \tag{10}$$
3. Calculate the current total share price Val($\mathbb{x}$) using $\mathbb{x}$ and a reasonable value calculated in the same way as stylized trading agents.
4. Calculate the new budget limit B.
$$B = \frac{1}{\frac{R-1}{2} + 1}\text{Val}(\mathbb{x}) \tag{11}$$
5. Under the budget limit B, re-optimize the portfolio and update $\mathbb{x}$.
6. Check the equation:
$$\text{CAR}(\mathbb{x}) \geq 0.08. \tag{12}$$
7. If the portfolio still violates Eq. 12, go to step 1 again. If not, $\mathbb{x}$ is the final position, which does not violate the CAR regulation.

2.6 Parameters

All agents have parameters. Some parameters were decided beforehand; others were decided by conducting a parameter search over a number of simulations. The agent parameters decided by parameter search are

- Amount of cash per market that each agent holds
- w_F^i: Weight for fundamentalist
- w_C^i: Weight for chartist
- w_N^i: Weight for noise

These parameters are decided by simulating with many parameter sets. In this study, the candidates for the amount of cash were 4,000, 6,000, 8,000, and 12,000, while the candidates for the weights were exponential distributions with means of 1.0, 3.0, 5.0, and 10.0. Then, the target kurtosis of the market price change was set to about 15 for five markets, 1,000 stylized trading agents, and 100 non-regulated portfolio agents. Kurtosis, κ, is defined with the logarithmic return r_t:

$$\kappa = \frac{\overline{(r_t - \overline{r_t})^4}}{\overline{(r_t - \overline{r_t})^2}^2} - 3. \tag{13}$$

Kurtosis was used in the parameter search, because a large kurtosis is a feature of “fat-tailed” distributions and it is a stylized fact characterizing real markets [7]. Here, events that occur rarely in accordance with a normal (Gaussian) distribution occur more often when they follow a fat-tailed distribution. Because $\kappa = 0$ for the normal (Gaussian) distribution, it is a good index for indicating a fat tail.

Table 1: Kurtosis of 5 min. interval [7]

Data	Kurtosis
S&P 500	15.95
Dollar/ DM	74
Dollar/ Swiss	60

Table 2: Kurtosis of daily price changes in Japanese markets

Data	Kurtosis
Nikkei 225	5.18
TOPIX	5.65
Compositions in Nikkei225	5.84 ± 3.16
Compositions in TOPIX	9.09 ± 9.84

According to Tables 1 and 2, the possible kurtosis seems to be under 20. The test with five markets, 1,000 stylized trading agents, and 100 non-regulated portfolio agents showed price changes with comparatively higher kurtosis than those of other simulations in this study. So, we assumed the target kurtosis to be about 15.

In addition, we checked for "absence of autocorrelations" and "volatility clustering", which are two of Cont's stylized facts [7].

The parameter search yielded the following results.

- Amount of cash per market that each agent holds $\rightarrow 6,000$
- w_F^i: Weight for fundamentalist $\rightarrow$ exponential distribution with mean 10.0
- w_C^i: Weight for chartist $\rightarrow$ exponential distribution with mean 1.0
- w_N^i: Weight for noise $\rightarrow$ exponential distribution with mean 10.0

3 Experiments

We designed two different experiments: one for assessing the effect of portfolio agents, the other for checking the effect of the CAR regulation.

Before explaining each experiment, we should explain the evaluation index. The index evaluates in how many steps the market price drops abnormally. We define "abnormal" as:

$$\mathrm{DV_t} = \ln\left(\frac{p_t}{p_t^*}\right) \leq -0.05. \tag{14}$$

In this equation, p_t means the market price and p_t^* means the fundamental price. Moreover, N_{DV} is defined as the number of steps in which Eq. 14 is true.

The common settings for the simulations were as follows.

- Pre-running length: 30,000 steps
- Simulation length: 60,000 steps
- Number of trials: 100 times per parameter set

3.1 Experiments for assessing effects of portfolio agents

First, using only stylized trading agents and non-regulated portfolio agents, as listed below, we experimented on the effect of portfolio agents.

- Stylized trading agents: 1,000 agents (fixed)
- Non-regulated portfolio agents: 0-100 agents (steps of 10 agents)
- Number of markets (number of assets): 1-10 markets (assets)

3.2 Experiments for assessing effects of the CAR regulation

Second, we included regulated portfolio agents. Here, the total number of non-regulated portfolio agents and regulated portfolio agents were fixed to 100 agents. We experimented by changing the ratio of non-regulated portfolio agents and regulated portfolio agents.

- Stylized trading agents: 1,000 agents (fixed)
- Non-regulated portfolio agents: 0-100 agents (varied in steps of 10 agents)
- Regulated portfolio agents: 100-0 agents (varied steps of 10 agents)
- Number of markets (number of assets): 1-10 markets (assets)

4 Results & Discussion

4.1 Effects of portfolio agents

Figure 3 shows the results of the experiments assessing the effect of portfolio agents.

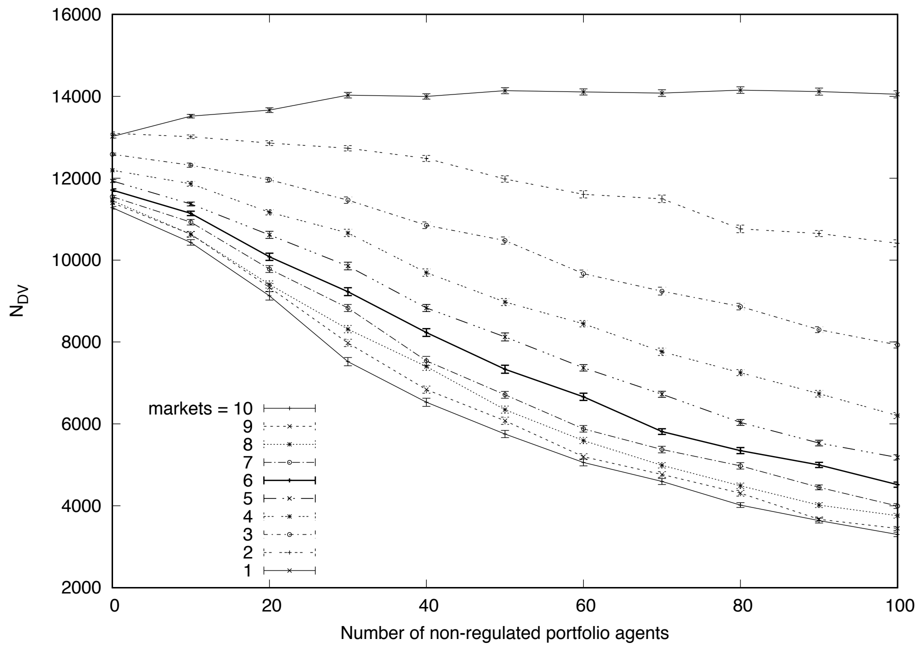

Fig. 3: N_{DV} of experiments assessing effect of portfolio agents. The horizontal axis is the number of non-regulated portfolio agents, and the vertical axis in the number of steps in which the market price is below $\exp(-0.05)$ times the fundamental price. Each series of plots shows results for the corresponding number of markets in the simulation. Error bars show 1σ.

According to Fig. 3, the more non-regulated portfolio agents there are in the markets, the fewer steps there are whose market price goes below $\exp(-0.05)$ times the fundamental price. This means non-regulated portfolio agents stabilize markets.

Ordinarily, portfolio optimization is thought to stabilize only individual trading returns. However, these results show that portfolio optimization can also stabilize whole markets.

In our opinion, because portfolio optimization can find market equilibria points, it can improve the efficiency of markets. In short, portfolio optimization might help to find the correct value for each asset, and it has a stabilizing effect on markets.

In addition, Fig. 3 shows that the more assets there are in portfolios, the more stable that markets become. Additionally, in the case of 5-10 markets, the stabilizing effect saturates.

These results also suggest that the number of portfolio agents is in the appropriate range to examine these effects, because the figure clearly shows changes in N_{DV}.

4.2 Effects of CAR regulation

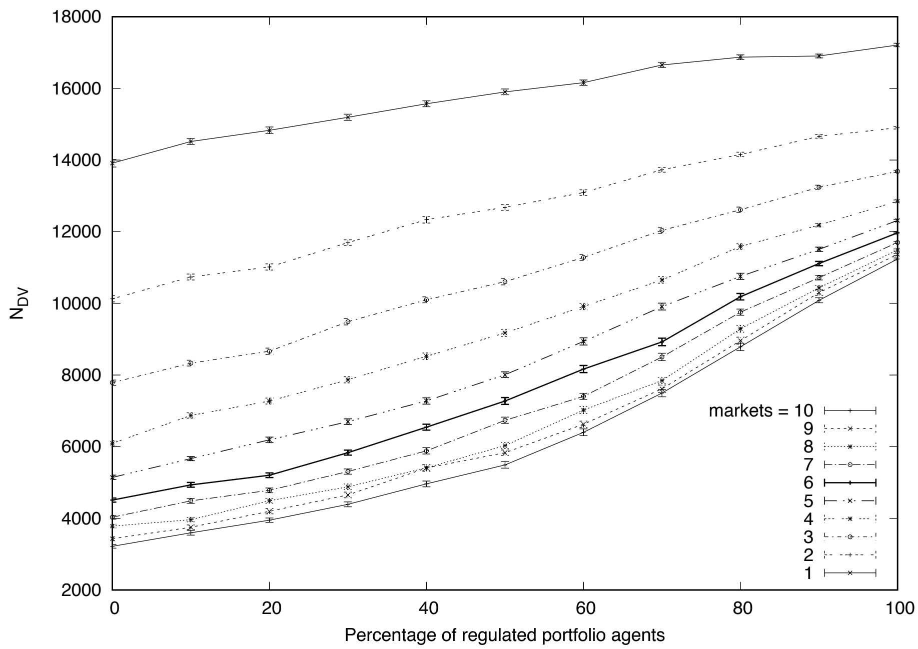

Fig. 4: N_{DV} graph assessing effect of CAR regulation. The horizontal axis is the percentage of regulated portfolio agents among all non-regulated and regulated portfolio agents. The vertical axis is the number of steps in which the market price is below $\exp(-0.05)$ times the fundamental price. Each series of plots shows a simulation series for a certain number of markets. Error bars show 1σ.

The far left of Fig. 4 shows N_{DV} in the case that the percentage of regulated portfolio agents is 0%. The results here are under the same condition as in the case that the number of portfolio agents is 100 in Fig. 3.

According to this graph, regulated portfolio agents make N_{DV} larger, which means CAR regulation causes more and more price shocks.

Moreover, when the percentage of portfolio agents regulated by Basel is 100%, the difference in N_{DV} between the instances of one market and ten markets is very little. It suggested that CAR regulation can suppress the stabilizing effect of portfolio agents.

These results show that CAR regulation may destabilize markets.

Let us consider why this happens. CAR regulation would be invoked when market prices fall and risks of holding assets increase; this means that agents would have to sell their assets. In turn, the regulation would have more and more impact on other agents. Thus, under these conditions, selling would induce more selling and lead to significant price shocks.

Now, let us look for other effects of CAR regulation by examining Figs. 5, 6, and 7.

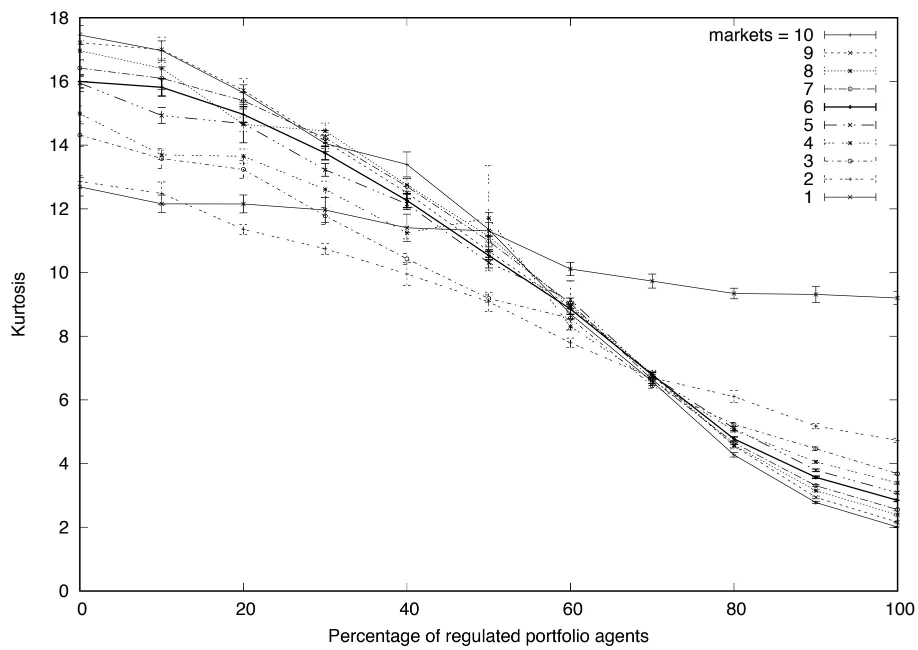

Fig. 5: Kurtosis of price changes in the experiments for assessing effect of CAR regulation. The horizontal axis is the percentage of regulated portfolio agents among all non-regulated and regulated portfolio agents. The vertical axis is kurtosis. Each series of plots shows results for a certain number of markets in the simulation. Error bars show 1σ.

Figure 5 shows the kurtosis of price changes. The definition of kurtosis is the same as in Eq. 13.

According to this figure, having more regulated portfolio agents decreases kurtosis. This suggests that CAR regulation eliminates the fat-tail tendency from markets.

The results depicted in the N_{DV} and kurtosis graphs suggest the following hypothesis: CAR regulation causes more price shocks and eliminates the fat-tail tendency, and CAR regulation depresses prices and decreases chances of market prices rising, because a rising market price indicates that there is more chance of the price decreasing. In addition, agents sell assets during sudden market price rises, because the chance of a price shock also increases in the CAR regulatory framework.

Thus, CAR regulation may depress whole markets.

Figure 6 shows the skewness of price changes. The skewness is defined as:

$$\gamma = \frac{\overline{(r_t - \overline{r_t})^3}}{\overline{(r_t - \overline{r_t})^2}^{\frac{3}{2}}}. \tag{15}$$

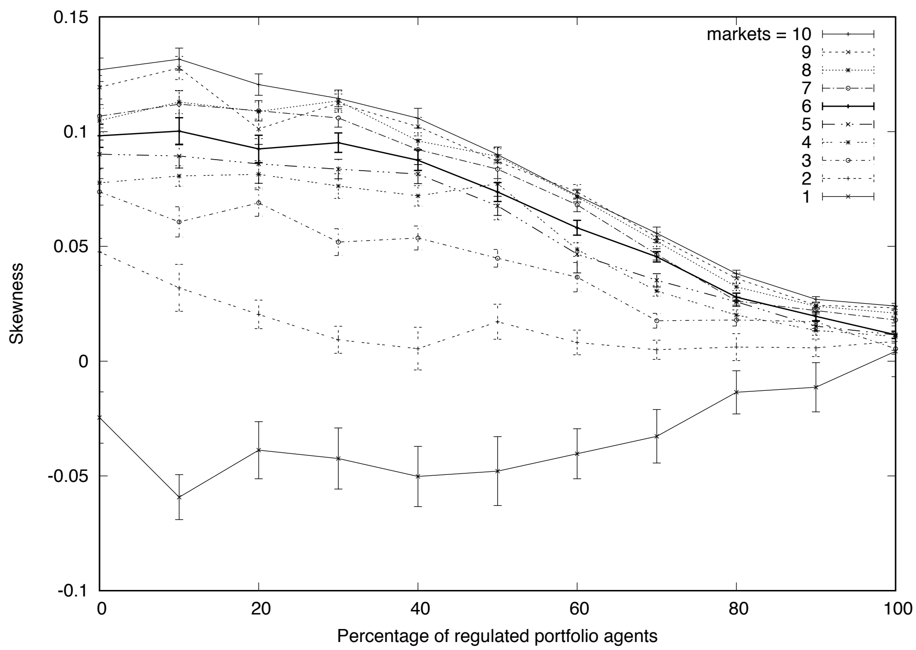

Fig. 6: Skewness of price changes in experiments for assessing effect of CAR regulation. The horizontal axis is the percentage of regulated portfolio agents among all non-regulated and regulated portfolio agents. The vertical axis is skewness. Each series of plots corresponds to a certain number of markets in the simulation. Error bars show 1σ.

Figure 7 shows the changes in mean DV_t. DV_t is defined in Eq. 14; it is the ratio of the market price to the fundamental price.

These two figures support the hypothesis that CAR regulation depresses whole markets. In Fig. 6, the skewness of price changes decreases as the number

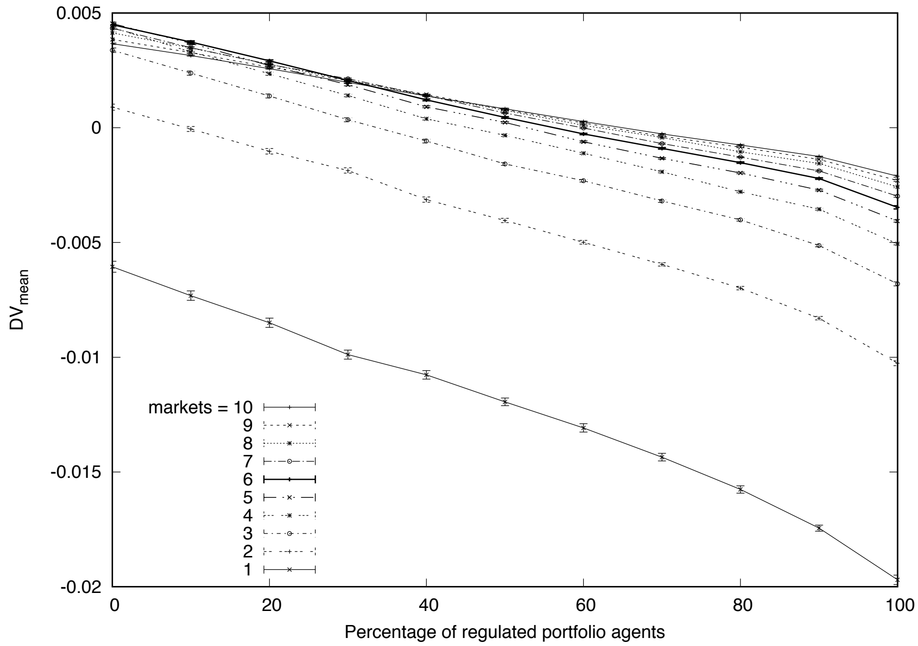

Fig. 7: Mean DV in experiments for assessing effect of CAR regulation. The horizontal axis is the percentage of regulated portfolio agents among all non-regulated and regulated portfolio agents. The vertical axis is mean of DV_t, which is defined in Eq. 14. Each series of plots shows results for a certain number of markets in the simulation. Error bars show 1σ.

of regulated portfolio agents increases. A decrease in skewness means the peak of the price change distribution shifts to the right (in the positive direction). In Fig. 7, a greater number of regulated portfolio agents depresses the mean of DV_t.

In summary, we suppose that three dynamics due to CAR regulation are at play: price shocks occur more often; prices recover in a step by step fashion; and price rises above the fundamental price occur less frequently. That price shocks occur more often is evident from the changes in N_{DV}. That prices recover in a step by step fashion can be expected from the first dynamic and that the skewness of price changes goes down with more regulated agents. The third dynamic, that price rises above the fundamental price occur less frequently, follows from that besides the drop in skewness, kurtosis also falls as the number of regulated agents increases.

5 Conclusion

We examined the effect of CAR regulation, as set out in the Basel regulatory framework, in agent-based simulations. By using agents who buy or sell at reasonable prices, agents whose strategy is portfolio optimization, and agents whose strategy is portfolio optimization under the regulation in artificial financial markets, we simulated two scenarios. The results lead us to the following conclusions:

- Adopting portfolio optimization as each agent's strategy stabilizes markets.
- The existence of a CAR regulation destabilizes markets.
- CAR regulation can cause significant price shocks.
- CAR regulation may suppress price increases.
- CAR regulation pushes down market prices.

Thus, we conclude that CAR regulation has negative effects for markets widely. Although it might be adequate to prevent systemic risks and chain bankruptcy, CAR regulation can have negative effects at least on assets markets and if significant price shocks happen, there is a possibility that bankruptcies are caused because of the price shocks.

Regarding future work, our finding that CAR regulation can suppress price increases is a new finding that should be the subject of verification. Moreover, we should examine other ways to calculate risk, e.g., by using the expected shortfall in the latest CAR regulation, instead of the VaR used in this study.

Acknowledgement

This research was supported by KAKENHI (no. 15H02745) and MEXT via Exploratory Challenges on Post-K computer (study on multilayered multiscale space-time simulations for social and economic phenomena).

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