Hush the Rush: Short-Selling Bans in Times of Stress

Armin Aminian

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Bamberg Economic Research Group
Bamberg University
Feldkirchenstraße 21
D-96052 Bamberg
Telephone: (0951) 863 2687
felix.stuebben@uni-bamberg.de
http://www.uni-bamberg.de/vwl/forschung/berg/

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Redaktion:

Dr. Felix Stübben[*]

[*] felix.stuebben@uni-bamberg.de

Hush the Rush: Short-Selling Bans in Times of Stress

Armin Aminian*[1,2]

[1]Economics Institute, University of Bamberg
[2]Bamberg Research Training Group on Bounded Rationality, Heterogeneity and Network Effects, funded by the Hans Böckler Foundation

Abstract

Short-selling restrictions are often enacted during financial turmoil to promote market stability, though most research highlights their negative impact on market quality. This study examines the stability and effectiveness of these restrictions in preventing market crashes in an agent-based financial market model, where the fundamental value is controlled. The model features heterogeneous traders switching between momentum-based and valuation-based strategies and a leveraged long-term investor. This design incorporates herding, extrapolate behavior, and deleveraging — key drivers behind market crashes. The findings corroborate previous research, indicating that short-selling bans hinder downward price discovery and lead to inflated prices. By distinguishing the effects above and below the fundamental value, the study shows that while positive price distortion increases, negative price distortion and crash severity decrease. This suggests that short-selling restrictions enhance price efficiency and stability below the fundamental value. Furthermore, the mitigation of crash dynamics along with corresponding behavioral drivers and network effects indicates that temporary short-selling bans contribute to systemic stability.

Keywords: Short-selling restrictions; Financial stability; Heterogeneous agents; Leverage; Herd behavior

JEL Classification: G19, G40

*Corresponding author. Email: armin.aminian@uni-bamberg.de

1 Introduction

Short-selling restrictions (SSR) are widely implemented during financial stress to maintain stability. Schinasi (2004) views price stability as crucial for the stability of the financial sector. For example, Adrian and Shin (2008) or Brunnermeier and Pedersen (2009) refer to asset market prices as the primary propagation channel during the Great Financial Crisis, as overlapping portfolios and falling prices led to deleveraging spirals. Despite SSR being imposed to promote stability, oddly enough, most SSR assessments focus on market liquidity and efficiency and find detrimental effects on both, which is strongly backed by theoretical elaborations.

However, research on the relationship between SSR and market or financial sector stability remains limited. This study seeks to address this gap by analyzing both efficiency and stability through an agent-based financial market model. The model incorporates the ability to control for fundamental value, thereby enabling a more comprehensive evaluation of SSR's effects.

Miller (1977) gives seminal theoretical reasoning for why SSR may distort the market price positively. His arguments are grounded in an efficient market for one asset with homogeneous agents and the idea that the price will eventually converge to its intrinsic value. Yet, traders do not know it and have heterogeneous expectations normally distributed around the fundamental value (F). With SSR, agents with negative information are excluded from trading, reducing supply and causing the price to rise above the F. Support for this so-called overvaluation hypothesis is provided by Harrison and Kreps (1978), Scheinkman and Xiong (2003) and Duffie et al. (2002). Diamond and Verrecchia (1987) attenuate it. They believe rational market participants would anticipate and correct inflated prices, so they argue that short-selling constraints only slow down price discovery.

Yet, recognizing regulators' intentions, Beber et al. (2020) suggest that research should give stability concerns more attention. It is axiomatic that price stability and efficiency are interrelated concepts. Price stability means prices remain within a benchmark range. The strong form of the Efficient Market Hypothesis by Fama (1970) claims markets fully incorporate all information. Fama (1991) develops his theory, adding that deviations from the efficient price occur due to market frictions. While the F is an almost philosophical concept, if one accepts it as a single price that reflects all available information and takes it as a stability benchmark, when a price is above its intrinsic value and falls, firstly, it can then be stated that efficiency and stability go hand in hand, and secondly, that downward frictions are not socially optimal.

However, it is known that agents are not rational and, due to behavioral factors, tend to extrapolate price movements. When scrutinizing human behavior, it is important to consider the motivations, abilities, and constraints.

The motivation of financial market participants is to maximize profits or minimize losses. Already Keynes (1936) linked greed and fear to market bubbles and crashes. Shiller (1987) survey results show that there are traders who only trade on price changes during crashes. In addition, Shiller (1981) shows that historical price trends can be disentangled from actual dividends. This extrapolate behavior is linked to herd behavior, where individuals imitate others. Market participants acting similarly create increased price pressure movements. Shiller and Pound (1989) see rational and non-rational causes for it. Bikhchandani and Sharma (2001) differentiate spurious herding, which is unintentional, similar behavior due to similar information, and intentional herding when investors choose to mimic others. The latter can especially be the case under uncertainty (Avery and Zemsky, 1998; Cipriani and Guarino, 2005).

The ability to realize desired orders depends on the resources at hand, like funds and assets, or the ability to borrow them. When investing with leverage, traders can place higher order sizes. At the same time, security borrowing allows them to short-sell assets they do not own. Geraci et al. (2018) uncover that short-sellers are particularly active on days with extremely high price drops. In this context, it is worth highlighting that short-selling can also be used as a technique for manipulative or predatory purposes. Bernheim and Schneider (1935) describe bear raids, where a group of investors collaborates to heavily sell a security, creating a strong negative price signal and potentially inciting panic to drive down its price. Another manipulative strategy is called short-and-distort, here traders short-sell a security and then artificially spread false or misleading information to drive down its stock price (Goldstein and Guembel, 2008; Mitts, 2020). Brunnermeier and Pedersen (2005) and Brunnermeier and Oehmke (2014) describe predatory short-selling, where sellers aggressively short-sell to harm a financially weak business, further driving down its stock price as its equity erodes. Next to short-selling, another ability-enhancing aspect is leverage, as it allows investors to amplify their purchasing power and can inflate prices. In turn, higher prices translate to more equity and more buying power (e.g. Geanakoplos (2010)).

The constraints of financial market players result from the fact that no one can bear infinite losses and alike endless risk. Thus, traders are restricted by legislation or risk management rules limiting their conduct. While leveraged traders experience more and more freedom during bull markets, during bear markets, the walls are closing in. Then leverage contributes to extreme price declines because it forces market participants to sell assets once markets turn down. When leveraged market-to-market portfolios experience losses due to price declines, a deleveraging feedback loop can start (also termed fire sales). This is because, on the one hand, higher negative returns increase risk measures and thus prudent equity requirements; on the other hand, equity erodes when prices fall, which both causes selling pressure and again pushes prices further down (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2008).

Keeping these behavioral factors in mind, a corrective downward price movement is likely to be prolonged below the F. If this is the case, efficiency and stability are both harmed and hence, downward frictions would be socially optimal to protect both. This being said, Hong and Stein (2003) state concerns about SSR, as they omit negative information from being factored into stock prices. This can amplify the formation of bubbles during bans and cause prices to drop more after bans end. So, they are concerned about a higher risk of market crashes due to SSR.

Against this background, this work aims to explore the mechanism of SSR and how they affect market dynamics, systematically addressing several key questions. First and foremost, how effective are SSR in reducing price drops far below the F? Second, are SSR an effective tool to contain behavioral spirals such as herding to extrapolate behavior and deleveraging? Third, to what extent are the concerns that a) SSR harm efficiency and b) promote the build-up of bubbles that burst when the ban is repealed, justified? Fourthly, how quickly should SSR ideally be deployed and removed?

The first question relates to market stability. The second question aims to evaluate the systemic stability significance of SSR, capturing the effect on network effects. The first question addresses concerns about stability and efficiency issues, and the second question pertains to the optimal use of SSR.[1] To address these questions, this work employs a robust analytical framework, incorporating rigorous variable selection and building on various research approaches, including empirical, experimental, and computational works.

Empirical research on SSR's effects is diverse, employing varying approaches and findings, with market quality measures, commonly in terms of liquidity or efficiency, being the primary focus. Stability, however, remains a somewhat marginalized concern. Yet, since stability and efficiency are strongly interconnected concepts, many indicators used to examine efficiency aspects also hold significant value when viewed through the lens of stability. These range from analysis of returns to market distortions and shifts. In the context of return analyses, valuable metrics are the skewness and the appearance of excess negative returns (Chang et al., 2007; Bris et al., 2007). The latter is typically defined as daily returns below two return standard deviations of a reference period. In addition, several methods have been established in the literature to examine how SSR affect asset performances subject to restrictions, comparing them with themselves in times in which they were not restricted or with other non-restricted assets in a common market at the same time. The basic idea behind these comparisons is to uncover frictions to the news incorporation process in return behavior by abnormal returns of individual assets to a reference market. Popular approaches are to compute the abnormal returns,[2] or the upside and downside cross-auto-correlations between individual stock returns and markets, to gauge friction by differences in the realization of beta factors (Bris et al., 2007; Boehmer et al., 2013; Beber and Pagano, 2013). While the results are somewhat heterogeneous, there is a discernible tendency towards the identification of positive distortion.
Hauser and Huber (2012) attribute this variability in findings to the likely inability to account for F using empirical methods. Thus, approaches that allow for controlled environments, such as experiments, are particularly meritorious. Grounded on the seminal financial market exper-

[1]Notably, the project is only concerned with the temporary use of SSR in times of stress, when agents tend to deviate most from rational behavior. The importance of short sales as elements of multiple financial instruments is indispensable, see e.g. Kosowski and Neftci (2014).

[2]See Bris et al. (2007), Chang et al. (2007), Boulton and Braga-Alves (2010), Harris et al. (2013), Beber and Pagano (2013), Bessler and Vendrasco (2022) and Spolaore and Le Moign (2023)

imental laboratory setup by Smith et al. (1988) with human participants, Ackert et al. (2005), Haruvy and Noussair (2006) and King et al. (1993) experimentally examine price effects of short-selling restraints. All authors obtain results depicting positive price distortions in the absence of the traders' ability to short-sell.

Further computational models have been utilized as a laboratory framework to explore SSR. This approach is particularly suitable for investigating the ability of SSR to contain market crashes. Farmer and Geanakoplos (2009) stress agent-based models are valuable for accurately modeling market behavior during stress and uncertainty. They feature individual agents with their own behavioral rules that allow them to account for bounded rationality and network effects. The collective system behavior emerges from the actions of agents, which are shaped by their interactions and environmental changes. Thus, this methodology enables the simulation of non-equilibrium phenomena, such as market crashes. Westerhoff (2008) picks up on the upsides of agent-based modeling, pointing out further advantages. He emphasizes the advantages of testing regulatory policies in financial markets. The benefits in this realm are numerous. It is noteworthy that the intrinsic value can be kept constant. In addition, agent-based financial models can mimic the price pattern of usual market behavior and unusual events in a controlled environment. This allows for generating as much data as required to examine policy effects thoroughly. In particular, this can be very useful in assessing the impact of regulatory means in rare situations such as market crashes. In addition, tracking all relevant variables and adjusting the policy parameters is possible. Hence, researchers can test the effect of policy parameters for different magnitudes and foster an understanding of the functioning and effects of the regulatory mechanism.

A series of scholars have conducted their analytical and numerical studies on agent-based finance models grounded on the seminal adaptive belief system model with fundamental and technical trading by Brock and Hommes (1998). Anufriev and Tuinstra (2013) examine short-selling impediments in the form of short-selling costs. The findings indicate that short-selling restrictions lead to price inflation and increased market volatility. Yet, under specific circumstances, it can also be seen that distortion below F is reduced. Furthermore, in 't Veld (2016) analyzes additional costs for short-selling and leverage, thereby restricting excessive selling and purchasing positions. To this end, he prepares two setups, one with fundamental and technical trading behavior in co-evolution and one with fixed weights of fundamentalists, optimists, and pessimists. His findings are distinct. First, mispricing and price volatility increase as the fundamental strategy is inhibited. Secondly, restrictions reduce volatility, but price distortion remains elevated. Dercole and Radi (2020) study the effectiveness of the uptick rule, a specific type of short-sale restriction that only allows short sales after a price increase. Notably, they base their assessment on regulators' goals to reduce price falls far below F and find that crash frequency as well as severity are mitigated. However, they anticipate criticism of their model for being overly deterministic and suggest that a stochastic model, which incorporates diverse trading strategies and emotions, would provide a more comprehensive framework.

Following up on this, the chosen setup does not only have stochastic components but also carefully incorporates the crucial behavioral drivers behind market crashes. The base model uses building blocks of Franke and Westerhoff (2012) and is further extended in the fashion of Schmitt and Westerhoff (2017) with a layer of individual agents. They all have their own asset stocks and individual trading orders guided by heuristic rules that are grounded on the key ideas of fundamental and chart analysis. In each period, traders reevaluate which strategy they want to follow based on recent profits, considerations of market circumstances, and other traders' behavior, making them prone to herd behavior. In addition, following the design of Aymanns and Farmer (2015b), one long-term investor is added. It only risk-adjusts its position based on a RiskMetrics Value at Risk model that captures the key principles of risk management for leveraged traders. This extension adds the pro-cyclical component of leverage to the model, which is also behind fire sale dynamics. Building upon this, the emerging price evolution replicates characteristics of real financial market dynamics as a fat-tailed distribution of returns, volatility clustering, absence of autocorrelation, a long memory effect in daily returns, and bubble and crash price patterns. For the analysis, SSR is implemented temporarily, in line with current regulatory frameworks, when the price significantly price plummets. The dynamics under SSR are then compared to simulations without SSR, specifically to samples where a hypothetical ban is imposed according to the enactment rules.

In general, the findings of previous works can be confirmed. In concrete terms, this means that prices are inflated when SSR are introduced, as downward price discovery is inhibited. Yet, given the stability focus of this work, this also means that SSR are shown to be effective in reducing downward market distortions and, thus, the severity of crashes. Likewise, SSR are shown to effectively mitigate behavioral network effects that exacerbate price declines, including herding and deleveraging. Since these factors fuel the propagation of shocks across markets, it can also be deduced that SSR can contribute to the containment of systemic risk. Moreover, the widespread concerns regarding SSR can be partly alleviated, since there are no price crashes when bans are lifted. In addition, as downward price movements are found to be impeded, it can be seen that above the F price efficiency is reduced and SSR lead to price bubbles. Yet, as SSR support corrective movement below the F, they also support price efficiency in this area. This supportive effect below the F is found to be stronger than the bubble effects above it and thus this work uniquely contributes that SSR can represent a net benefit gain in times of stress.

2 Methodology

In this section, the model structure is first presented. Next, the parameter settings and the model's validation are detailed. Finally, the dynamics of the model are discussed, with a focus on elucidating the underlying mechanisms that drive the model's behavior.

2.1 Base Model

The model's main skeleton is assembled using building blocks of Franke and Westerhoff (2012). Minor changes are made to the original time structure, and the here presented model is based on nominal prices instead of logarithmic prices. Additionally, the model's cornerstones are extended in two ways. The first extension is a layer with individual traders, following Schmitt and Westerhoff (2017). This enables the integration of individual trading and individual asset stocks, which is necessary for effective policy implementation. As a second extension, a representative leveraged long-term investor named ”bank” is introduced in the fashion of Aymanns and Farmer (2015b), which only adjusts its position to match the leverage rate to the market risk. This introduces the leverage factor as a driving force behind market dynamics.

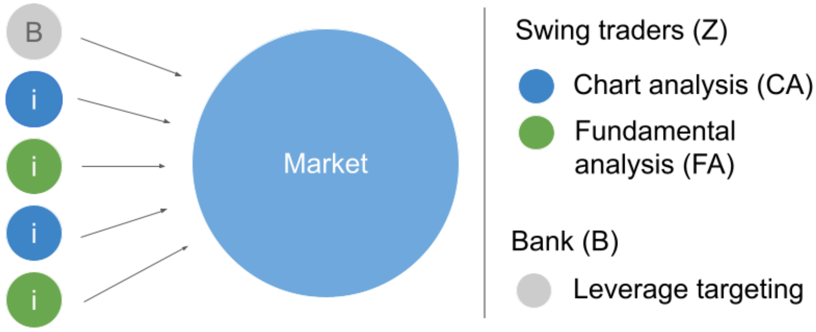


Figure 1: This model overview illustrates the market structure. The market is provided by the market maker. All one hundred market participants are given by N = {B, Z}. B is one representative leveraged long-term investor. The remaining ninety-nine are swing traders given by $Z = \{i_1, i_2, \ldots, i_{99}\}$. For reasons of space, these are shown in reduced numbers. It should also be noted that they are constantly adapting their strategy (chart analysis or fundamental analysis) and that the strategy distribution depicted here is only exemplary. Against this background, the price evolution results from extrapolating, mean-reverting, and leverage-adjusting trades.

2.1.1 Market mechanism

The model's heart is the price adjustment function. The price of the asset is based on the previous price, P_{t-1}, and adjusts according to aggregate excess demand, AD_t, scaled by parameter α. Following Day and Huang (1990), the market maker equation is:

$$P_t = P_{t-1} + \alpha AD_t \tag{1}$$

Intuitively, aggregate excess demand is calculated as the sum of all individual trading orders. This is the demand of the bank, D_t^B, and all swing traders, D_t^i. The equation for the aggregate demand is:

$$AD_t = D_t^B + \sum_{i \in Z} D_t^i \tag{2}$$

2.1.2 Short to medium-term speculators

In each simulation step, swing trader i reconsiders buying or selling based on the trade order, $TR_t^{S,i}$, derived from one of the strategies, $S = \{CA, FA\}$, fundamental analysis (FA), or chart analysis (CA). The model generates hypothetical trading orders for both strategies. Which one realizes is determined by an indicator function, I_t^i, showing the strategy decision in the demand function, D_t^i. This is given by:

$$D_t^i = \begin{cases} TR_t^{FA,i} & \text{if } I_t^i = FA \\ TR_t^{CA,i} & \text{if } I_t^i = CA \end{cases} \tag{3}$$

Prior to examining the selection process, the strategies are briefly introduced. The fundamental strategy is based on the idea that the price will eventually converge to its F.

$$TR_t^{FA,i} = \beta_{FA}(F - P_{t-1}) + \varepsilon_t^{FA,i} \tag{4}$$

The chart analysis trading signal is grounded on the belief in a continuation of the current price trend.

$$TR_t^{CA,i} = \beta_{CA}(P_{t-1} - P_{t-2}) + \varepsilon_t^{CA,i} \tag{5}$$

Where β_S are reaction parameters, F is the fundamental value, and $\varepsilon_t^{S,i}$ are noise terms. The conceptualization of the noise terms is inspired by Schmitt and Westerhoff (2017), who assume a correlation between the noise terms. Following this, the noise term comprises both a macro and an individual component. The macro component can be understood as misinformation, disinformation, or spurious herding. The individual component accounts for bounded rationality and, in the case of chart analysis, also for various trading rules that fall under this umbrella term. $\chi_t^S \sim \mathcal{N}(0, \sigma_S)$ reppresents the cross-trader i.i.d noise term, and $\chi_t^{S,i} \sim \mathcal{N}(0, \sigma_S)$ is the individual i.i.d noise term.

$$\varepsilon_t^{S,i} = (1 - h)\chi_t^{S,i} + (h)\chi_t^S \tag{6}$$

Subsequently, the approach for selecting the mentioned strategies is presented. Boiled down, traders evaluate the so-called fitness of the strategies to determine the choice probabilities with which the decision is made. The fitness measures, $U_t^{S,i}$, are specified as:

$$U_t^{CA,i} = c_G G_t^{CA,i} + c_H H_t^{CA}; \tag{7}$$

$$U_t^{FA,i} = c_G G_t^{FA,i} + c_H H_t^{FA} + c_M M_t; \tag{8}$$

These fitness functions comprise several components: a herding effect, H_t^S, a misalignment effect, M_t, and hypothetical trade gains, $G_t^{S,i}$. Correspondingly, the parameter, c_H, denotes the herding effect strength, c_M, captures the impact of misalignment, and c_G, determines the influence of hypothetical trade gains.

$$G_t^{S,i} = \mu \cdot G_{t-1}^{S,i} + (1-\mu) \cdot (P_{t-1} - P_{t-2}) \cdot TR_{t-2}^{S,i} \tag{9}$$

$G_t^{S,i}$ is the profit memory function for trader, i, of strategy, S, at time, t. Since traders want to maximize their profits, they prefer using the trading strategy that recently gave them the highest hypothetical gains. In this vein, the equation represents a weighted average of hypothetical profits, preferentially taking into account short-term past profits. The first term, $\mu \cdot G_{t-1}^{S,i}$, represents the share of the previous profits' value, determined by the weight parameter, μ. The second term, weighted with $(1-\mu)$, represents the most recent observable hypothetical profit. To compute this, the agents consider the hypothetical trade orders of both strategies two periods ago, $TR_{t-2}^{S,i}$, regardless of execution. The orders are served at the end of the same period in which they enter the market at P_{t-2}. As traders are only able to observe the price change to P_{t-1} in t, they only then recognize whether they made profits or losses.

As already elaborated, herding behavior is a well-observed phenomenon in financial markets. This is implemented in the model by assuming traders know how the other traders have traded in the last period. The corresponding value of the term is determined using a program code. A function counts the number of times the strategy symbol appears in the array from the previous period. To compare the strategies directly, the relative share is calculated by dividing by the number of swing traders.

$$H_t^S = \frac{\sum_{i \in Z} 1(I_{t-1}^i = S)}{|Z|} \tag{10}$$

Furthermore, agents consider the absolute misalignment between the last observable price and the fundamental value. The intention behind this term is that once traders perceive the distortion to be unreasonably high, they expect a correction. To keep the exponential nature of the relation that is assumed by Franke and Westerhoff (2012), who use log prices, a transformation parameter, τ_{exp}, is added.[3]

$$M_t = (\tau_{\text{exp}}(F - P_{t-1}))^2 \tag{11}$$

Since the relative difference in fitness is the pertinent factor, computing the disparity between the two equations simplifies the model.

$$U_t^i = U_t^{FA,i} - U_t^{CA,i} = c_G(G_t^{FA,i} - G_t^{CA,i}) + c_H(H_t^{FA} - H_t^{CA}) + (c_M M_t) \tag{12}$$

Given the fitness considerations, the likelihood that a strategy is chosen is determined by the choice probability function, Π_t^i, following Brock and Hommes (1998).

$$\Pi_t^i = \frac{1}{1 + \exp[\delta U_t^i]} \tag{13}$$

δ represents a choice intensity parameter. In the next step, a program function draws one strategy with the given probabilities and returns the corresponding strategy symbol. Here, this is illustrated with the indicator function, (I_t^i):

$$I_t^i = \begin{cases} FA & \text{with Prob } \Pi_t^{CA,i} \\ CA & \text{with Prob } \Pi_t^{FA,i} \end{cases} \tag{14}$$

2.1.3 Long term investor

To add a pro-cyclical leverage component to the model, similar to Aymanns and Farmer (2015b), one so-called bank, B, is introduced, which can be understood as a representative long-term investor that only adjusts the size of its total positions according to the perceived risk measure by a scaled RiskMetrics Value at Risk model, VaR_t.

[3]This transformation is necessary, as in the original set-up the fundamental value is zero, and P can become negative. Yet, this would render the subsequent introduction of a long-term trader unfeasible, as this trader always operates based on maintaining a positive portfolio value.

$$VaR_t = 2,33(\frac{1}{L}\sum_{t-L}^{t}(r_{1,t} - \bar{r})^2) \tag{15}$$

The term in parentheses after the Z-score 2.33 is a volatility estimate. $r_{1,t}$ is the return of one day. Returns are computed as percentage changes from P_{t-2} to P_{t-1}. $\bar{r}$ is the mean of all returns, and by assumption 0. L is the look-back period, which determines how far into the past returns are considered. The Z-score, in turn, adjusts the volatility estimate to correspond to a 95 percent confidence level in a standard normal distribution, ensuring that the calculated loss estimate is not exceeded with a probability of 5 percent. Based on this VaR, the bank determines its target leverage rate.

$$LR_t^{Tar} = \Psi VaR_t \tag{16}$$

In this equation, Ψ represents an additional scaling parameter to put the leverage target at a reasonable height, following Aymanns and Farmer (2015b) closely. LR_t^{Tar} is updated at the beginning of every period in reaction to the new price that is determined at the end of the last period, which directly affects the bank's equity.

For the leverage adjustment trading rule, a model-compatible approach is designed. To this end, the bank obtains an account, tracking among others, the equity, E, and debt, DB, amounts. Appendix A details the bank's account structure, the derivation of the trading rule, D_t^B, and economic interpretation.

$$D_t^B = \frac{LR_t^{Tar}E_{t-1} - DB_{t-1}}{P_{t-1}} \tag{17}$$

2.1.4 Model validation

Model validation is essential in ensuring the accuracy and reliability of simulation results. It involves comparing the simulation results with statistics of real-world data to determine the degree of agreement between them. The forthcoming simulation dynamics are based on the parameter setting presented in Table 1. Day-to-day financial market statistics possess a multitude of stylized facts. The model has been carefully calibrated to replicate the most prominent statistics of real financial market dynamics and thus is understood to present a sound framework for policy experiments. To the end of validation, it is focused on aspects of return behavior such as fat tails, volatility clustering, absence of autocorrelation, and long memory returns.

Further, in Figure 2 the model output is presented, demonstrating that it is able to replicate these stylized facts. The corresponding simulation run is based on 5,000 observations, and a transient period of 1,000 periods has been erased. The fundamental value has been set to 1. As the model is calibrated to replicate daily data, the output corresponds to a time horizon of roughly 20 years.

Prices in financial markets do not always reflect their fundamental value. In fact, regular periods of pronounced divergence emerge in the form of bubbles and crashes. In significant parts, these dynamics are market-endogenous, as backed by numerous laboratory experiments. For comprehensive overviews, see Palan (2013) or Porter and Smith (2003). The first panel displays the model's price evolution. The model generates a bubble and crash pattern and lasting phases of under- and overvaluation of over 30 percent.

The second panel presents the relative daily price changes (returns). Note that as the fundamentals are held constant. Nevertheless, there are excessively high price movements, reaching as much as over 10 percent.

Although the return distribution in financial markets is bell-shaped like a normal distribution, it differs in a particular way. This phenomenon, commonly described as fat tails, refers to a distribution that shows more probability mass in the center and its tails. From the histogram in the center, it is clear that this is the case in the model. To obtain a better impression of the tails, the hill index is computed. Its calculated value is 3.39, suggesting an accurate approximation of actual financial data.

Financial markets' price paths are close to a random walk, or put differently, price movements are uncorrelated. The autocorrelation function of raw returns is depicted in the second plot from the bottom up. Since, for almost all lags, the values are within the ± 0.05 bands, which is the 95 percent confidence threshold, the autocorrelation of the raw returns is not significant. Therefore, the price evolution is random and entirely unpredictable.

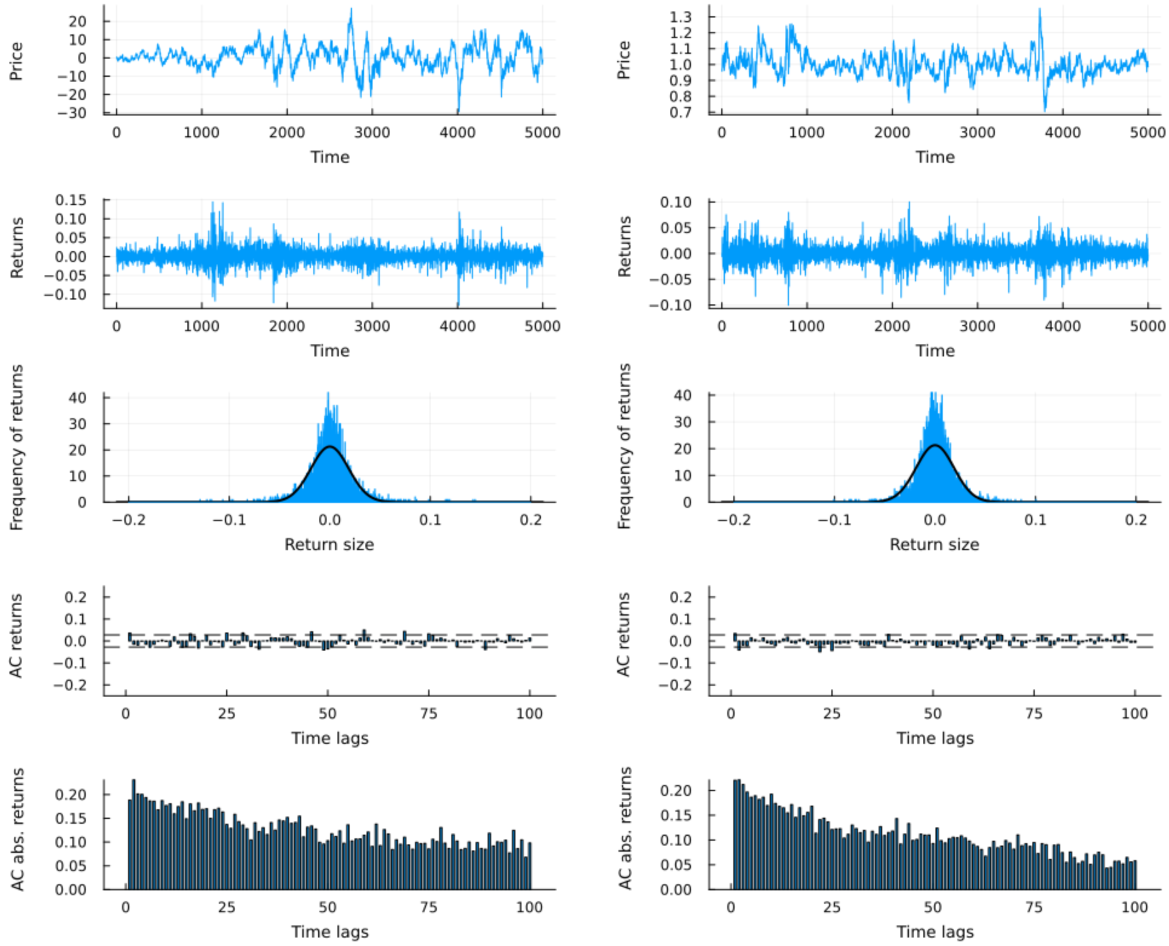


Figure 2: Stylized facts: The graph illustrates a comparison between the observed patterns in financial market data of BMW shares (on the left) and a representative simulation run generated by the model (on the right). The actual data is sourced from LSEG/Refinitiv, encompassing 5000 periods spanning from December 1, 2004, to January 30, 2024. To enhance comparability between the upper two price series plots, the price movements were detrended using the 200-day moving average as an approximation for the fundamental price.

Table 1: Parameter Settings

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
α	0.0005	τ_{exp}	20	L	200
β_F	1	c_M	0.05	Ψ	4.5
β_C	1	c_H	10	F	1
σ_F	0.25	c_G	650	AS_1^i	20
σ_C	1.75	δ	1.67	AS_1^B	300
h	0.5	μ	0.99	DB_1^B	150

Despite this unpredictability, in real markets, it can be observed that minor price movements are more likely to be followed by minor price movements and vice versa. This is known as the long-memory effect. Price dynamics exhibit episodes of low volatility and episodes of high volatility. Therefore, clusters of distinct volatility emerge. This phenomenon is already apparent from the top of the second graph. Additionally, the auto-correlation function for absolute returns over a hundred lags is displayed in the bottom panels for sound evidence. It is positive and shows a steadily declining form. Volatility levels seem to persist and vanish, demonstrating long memory and volatility clustering.

2.1.5 Discussion of model design and dynamics

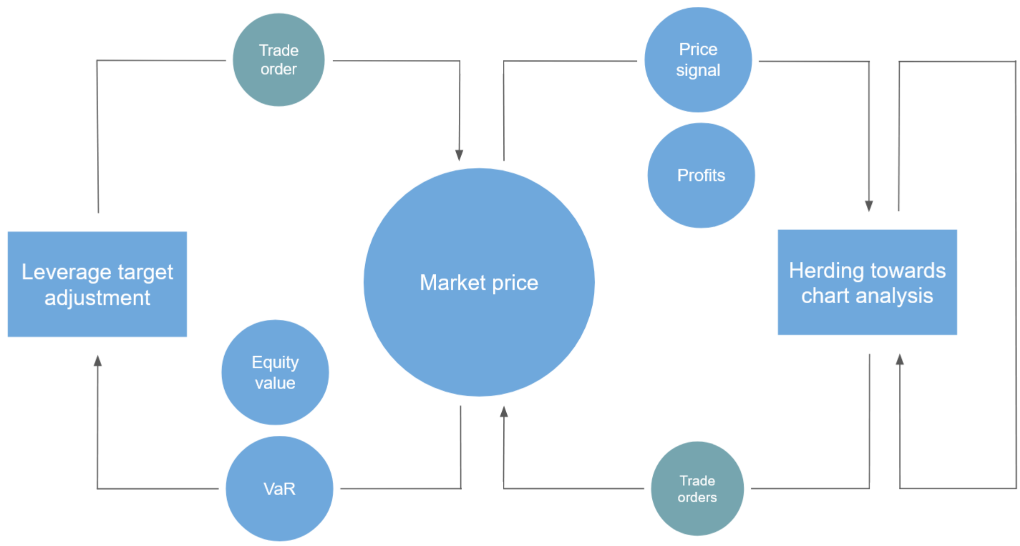


Figure 3: The propagation effects and how they reinforce themselves and each other, as specified in the model. On the right-hand side (RHS), ”herding” and ”extrapolate behavior” are merged into a single aspect, “herding towards chart analysis”. On the left-hand side (LHS), there is a leverage adjustment. The two factors are linked via the market price.

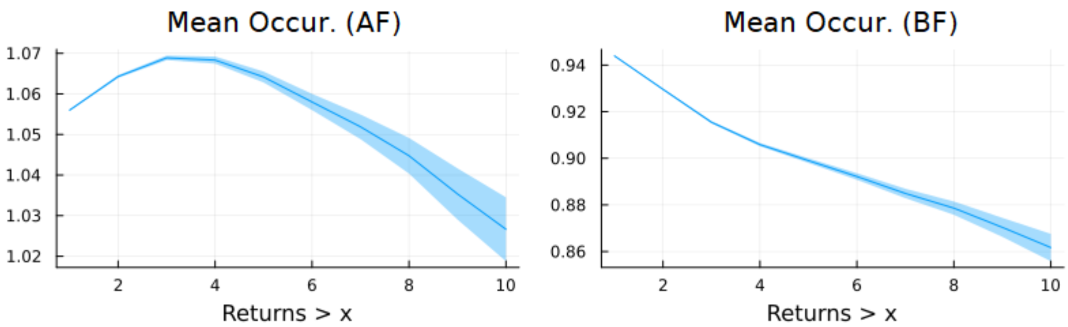
Subsequently, the model dynamics will be discussed to provide an understanding of the underlying behavior. Initially, it is important to note that given the demonstrated random walk nature of price dynamics, the noise terms hold significant relevance. Of course, these do not explain the replication of the other characteristics. Yet this will be done now, by linking the movements of the price evolution to the underlying metrics and laws of motion in the model setup. The behavioral factors that drive crash dynamics in reality have already been elaborated.

For the replication of the model, the strategy decision of every trader in each period plays a key role. Different strategy distributions result in varying volatility levels and market drifts. As previously elaborated, for the strategy choices, the outputs of individual fitness functions are compared. Its components change in size, allowing the agents to adjust their behavior to the current market situation. The pro-cyclical leverage component in the model additionally promotes these dynamics.

To illustrate how market trends and, consequently, crashes (or bubbles) emerge in the model, an exemplary narrative is presented, supported by Figure 3, which illustrates all the influence channels in the model. As a starting point, we envision a scenario in which chartists hold a larger market share and go short. Due to their dominance, the price goes down. In the next period at the RHS, several factors will need to be considered. The price drop strengthens the trading signal and increases the probability of a stronger sell-off. In addition, the market dominance of the bearish chartists has an informational spillover. Hence, due to herding considerations, the attractiveness of the chartist rule makes it more likely that more agents will choose to extrapolate the price movement with a stronger signal in the next period. At the LHS, at the same time, when the price goes down, this has two effects on the bank's position. First, all price changes affect the market risk measure. Thus, when a comparatively high negative price change occurs and significantly affects this measure, the bank would have to risk-adjust its position and sell assets. Second, the banks' equity decreases whenever the price decreases. Consequently, it has to sell assets to meet its leverage target again. This additional selling pressure, in turn, strengthens the negative price signal in the chartist trading rule. In the next time step at the RHS, the fitness function of the chartist rule is elevated by the agents realizing (hypothetical) profits. Accordingly, the spirals reinforce themselves and one another. While this exemplary story provides a good understanding of the underlying laws of motion and how market trends arise, the realization of the noise term can weaken or reverse a trend, depending on its size. However, when the market is in a regime where chart analysis is the prevailing strategy and the bank's risk measure is increased, the trade orders entering the market are, in general, higher. This increases the likelihood of trend fostering and higher market distortions.

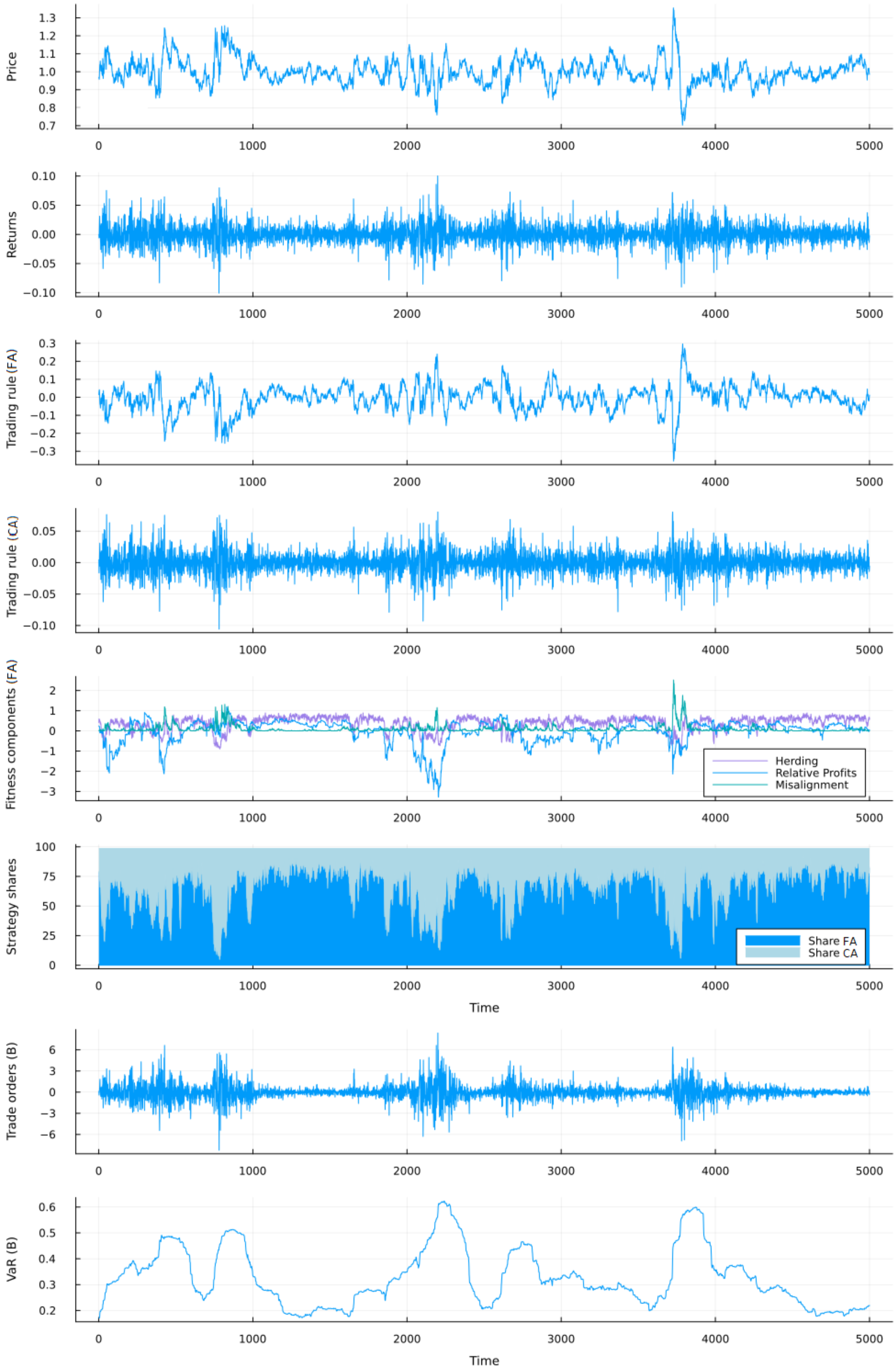
Figure 4 illustrates the power of the described mechanisms by showing the bias in the occurrence of negative returns of different sizes. Specifically, the mean prices at which different sizes of negative market returns occur in 1000 simulation runs are plotted for the case above F (AF) and below F (BF). The curves both show an initial bow, indicating that smaller returns occur more frequently, closer to F, which can be attributed to the distinct regimes and volatility clusters. Much more interesting, however, after the bows, in both cases, the mean occurrence price of negative returns exhibits a stronger negative bias, the stronger the negative returns are, demonstrating the importance of the downward spirals in the model dynamics.

Figure 4: Mean occurrence prices of negative returns by size



To further deepen the comprehension of the model, Figure 5 displays market and trading behaviors as well as underlying pertinent metrics. Panels 1 and 2 show the price and return evolution of Figure 2. The corresponding behavior of swing traders is depicted in panels 3 through 6, while the bank's activities are shown in panels 7 and 8. A detailed examination of the juxtaposition of metrics allows for an understanding of co-dynamics. For example, it can be seen how the crash (/bubble) formations (e.g., around periods 2200 and 3800) coincide with more intensive trading activity of chartists and the bank. For the chart analysis, the trading order size and the market share rise, alongside the relative hypothetical profits and the herding term turning in favor of the chart analysis. Additionally, the bank's VaR/leverage target and leverage adjustment orders are demonstrated to be simultaneously amplified during these phases. Furthermore, it is evident that during periods of pronounced market distortion, the misalignment term experiences a sharp increase. Consequently, numerous swing traders anticipate a price reversion, pivot toward fundamental analysis, and promote a market correction.

Figure 5: Functioning of the model



3 Analysis

The following section scrutinizes the effects of SSR. In the first step, the experimental setup is presented, showcasing how the policy mechanism is implemented. In the second step, the observatory variables are introduced, and their results are laid out.

3.1 Experimental setup

To evaluate the policy effects, the model is run without and with SSR in place in series. To have a significant number of observations, the model is simulated for 5000 periods, repetitively 5000 times, for both scenarios. To have appropriate comparison data, it is only looked at times when the restrictions bind, and respectively at phases in which the policy would have been hypothetically in force. To address the concerns raised by Hong and Stein (2003), which suggest that bubbles emerge and burst after restrictions are lifted, the two trading weeks following the ban periods are also tracked.

The enactment of SSR is exercised in line with the EU regulation 236/2012, giving regulators the power to set SSR in place in case of ”exceptional circumstances” or a ”significant fall in the price”. Based on this, SSR are implemented if the price drops by more than the policy threshold θ in one period.[4] For the initial analysis, θ is set to -5 percent but is later varied to test the robustness of the results for different values. The ban is technically implemented by setting the ban parameter ρ for 20 periods from ”inactive” to ”active” after the threshold is exceeded. This policy length is only an initial value, and the effects are subsequently tested for their sensitivity to changes in this parameter, Λ. 20 periods are used as this number corresponds to one month in trading days. This is the ban length most EU countries chose at the start of the COVID-19 pandemic, for an overview see Bessler and Vendrasco (2021).

Transitioning to the technical implementation in the model, let’s recall that in its simple form, short-selling is a trading strategy in which an investor sells a borrowed security with the expectation that its price will fall and repurchase it later. To temporarily prohibit this practice in the

[4]Policy phases that would extend beyond the end of the simulation run and are artificially shortened by this are not taken into account, as the length varies and this could result in distorted values. The policy mechanism is deactivated in the transient phase.

model, traders' sale orders are limited to the number of shares they hold. This is accomplished in two steps. First, asset stocks, AS_t^i, in the form of equation (18) are introduced for all traders. The two cases in the equation refer to policy inactivity and activity. For SSR to be in place, the added maximum function ensures that the asset stock will not be negative. Economically, this means that agents can no longer engage in security lending.

$$AS_t^i = \begin{cases} AS_{t-1}^i + D_t^i & \text{if } \rho = \text{inactive}, \\ \max\{AS_{t-1}^i + D_t^i, 0\} & \text{if } \rho = \text{active}. \end{cases} \tag{18}$$

Second, trade order sizes are limited on the downside to the amount AS_t^i. To this end, equations (4) and (5) are substituted by (19) and (20). Hence, swing traders can only sell assets that they have in their portfolio and can not short-sell anymore.

$$TR_t^{F,i} = \begin{cases} \beta^F(F - P_{t-1}) + \varepsilon_t^{F,i} & \text{if } \rho = \text{inactive}, \\ \max\{\beta^F(F - P_{t-1}) + \varepsilon_t^{F,i}, -AS_{t-1}^i\} & \text{if } \rho = \text{active}. \end{cases} \tag{19}$$

$$TR_t^{C,i} = \begin{cases} \beta^C(P_{t-1} - P_{t-2}) + \varepsilon_t^{C,i} & \text{if } \rho = \text{inactive}, \\ \max\{\beta^C(P_{t-1} - P_{t-2}) + \varepsilon_t^{C,i}, -AS_{t-1}^i\} & \text{if } \rho = \text{active}. \end{cases} \tag{20}$$

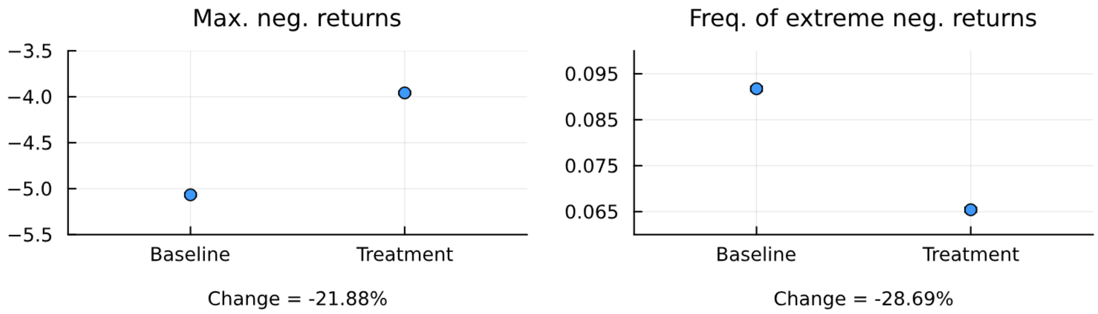
3.2 Metrics and results

The analysis centers on the impact of SSR on the effectiveness of containing crashes (far) below the fundamental value and the underlying behavioral factors. Additionally, a comprehensive investigation of common concerns is conducted, covering efficiency losses and post-restriction crashes. Ultimately, with the objective of improving the understanding of the optimal design and utilization of SSR, its impact is tested for different policy parameters. All estimates are provided as means of the simulation runs with 95 percent confidence bands. However, to improve readability, only the variable names will be used subsequently when referring to metrics. Further details on the variable design are laid out in Appendix C.

3.2.1 Analysis of Crash Prevention

To quantify the effect of SSR on crash formations, a set of metrics is considered. These cover the maximum negative returns, the frequency of extreme returns, trade order interactions to gauge the impact on the underlying behavioral drivers, and the negative price distortion to measure the severity of crashes far below the fundamental value.

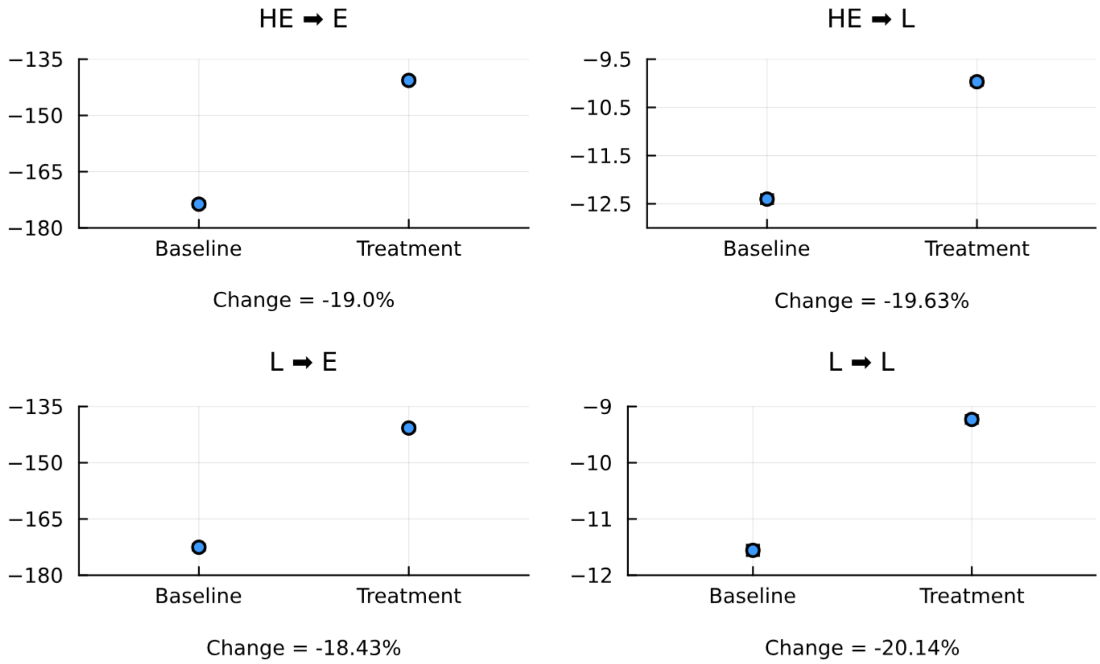
Figure 6: Impact of SSR on return crash pattern



As a first step, it is focused on the effectiveness of SSR in containing crash return patterns. Figure 6 contains the maximum negative returns and the frequency of occurrence of extreme returns, expressed as the coefficient per one hundred periods. Extreme negative returns are defined as $r < -3$ percent, as this threshold is equivalent to twice the standard deviation of returns. It can be observed that SSR reduces the extent of both variables. The maximum negative returns decrease from the baseline to the treatment by 21.88 percent, from 5.07 to 3.96 percent. The frequency of extreme negative returns also drops from 9.17 to 6.54 occurrences of extreme price falls per one hundred periods, representing a 28.69 percent decrease.

In the next step, the underlying behavioral spirals leading to crashes and extreme price returns are examined in detail. As elaborated, excessive price crashes are caused by the behavior of financial market participants and network effects that can result in vicious spirals. It is worth noting that SSR's potential effectiveness in mitigating these propagation effects also underscores its relevance within the context of systemic stability. The interaction channels, as delineated in the model and illustrated in Figure 3, along with the corresponding exemplary story, form the basis of this analysis.

Figure 7: Impact of SSR on sell order interactions



In Figure 7, the impact of SSR on the self-referential and mutual effects of selling orders on both sides of the Figure 3 is depicted. Specifically, the order sizes shaded green in the chart serve as analysis variables. As market crashes are extreme downward scenarios, the maximum sell orders are considered. At this point, it is also valuable to recall that only swing traders are affected by the restrictions since the bank only adjusts its position. To track the effects of herding toward extrapolate behavior, the sell order sizes by the bank and swing traders using chart analysis are collected. If chart analysis was the dominant strategy in the previous period, the collective order size of traders using it was negative. This provides a metric that jointly allows the capture of the effect of the trade order and the market share size of chartists. Likewise, the impact of the leverage adjustment sell orders is measured using both trade order sizes if the leverage adjustment order was negative in the previous period.

First, it is focused on the effects of herding toward extrapolate behavior. The imposition of SSR brings about a notable shift in the maximum sell orders executed by chartists following a negative period with dominant chartism (HE $\rightarrow$ E). With a significant decrease of -19.0 percent, from -173.66 to -140.66. In parallel with the enactment of bans, there is a reduction of

19.63 percent in the maximum leverage adjustment trade size following a period of dominant chartism (HE $\rightarrow$ L), from a baseline mean of -12.4 to -9.97. Now the indirect effects of SSR on deleveraging orders and its impact on itself and extrapolate selling are scrutinized. The findings indicate a decrease in the maximum trade order sizes. The values for the maximum negative order size by agents adhering to the chartists' rule (L $\rightarrow$ E) witness a decrease of -18.43 percent, from -172.54 to -140.74. Similarly, the metric for the bank's maximum negative order size (L $\rightarrow$ E) decreased from -11.56 to -9.23 under treatment by -20.14 percent.

Ultimately, to gauge the effect of SSR's negative market distortion on crash severity, the market distortion BF is examined. Distortion serves as a critical metric as it illustrates the deviation from the intrinsic value. Distortion is measured as the percentage difference of the price to F. The average and maximum values are specifically measured. The former is intended to give a general impression, and the latter to show extreme cases.

Figure 8: Impact of SSR on price distortion metrics

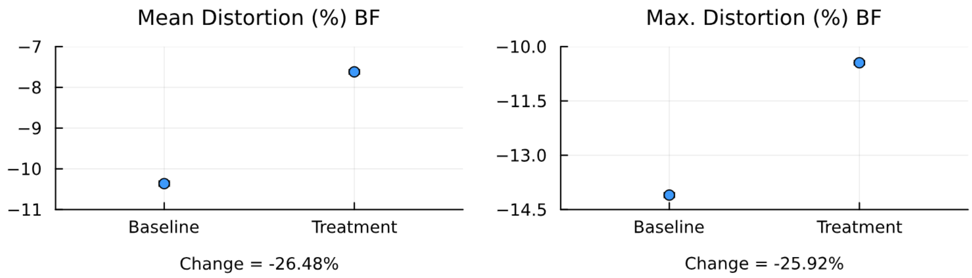
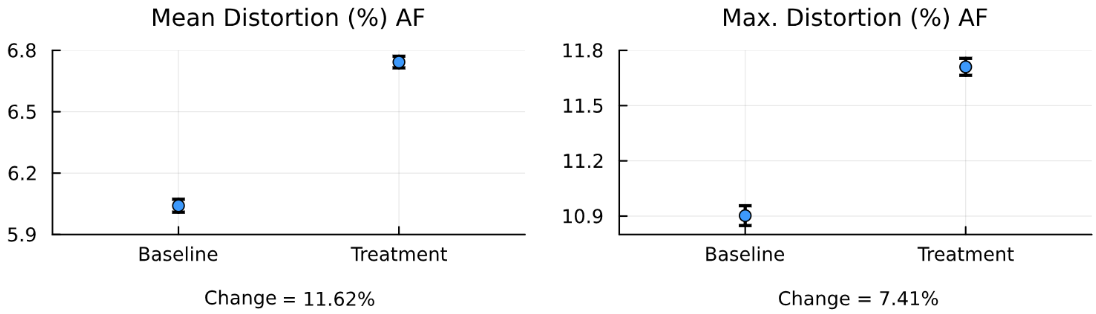


Figure 8 presents an overview of distortion metrics below the intrinsic value. Due to SSR, the mean distortion exhibits a decline of -26.48 percent from -10.36 to -7.62 percent. Further, negative maximum distortion decreases from -14.1 to -10.45 percent, and hence by -25.92 percent in response to SSR.

3.2.2 Analysis of Concerns

Given the widespread concerns about the implementation of SSR, including price inflation and subsequent price crashes when SSR are repealed, the subsequent analysis examines to what extent these worries are justified. The measures cover distortion above the fundamental value, the return behavior both above and below the fundamental value, and an analysis of short-term price trends following the repeal of SSR.

Figure 9: Impact of SSR on crash pattern

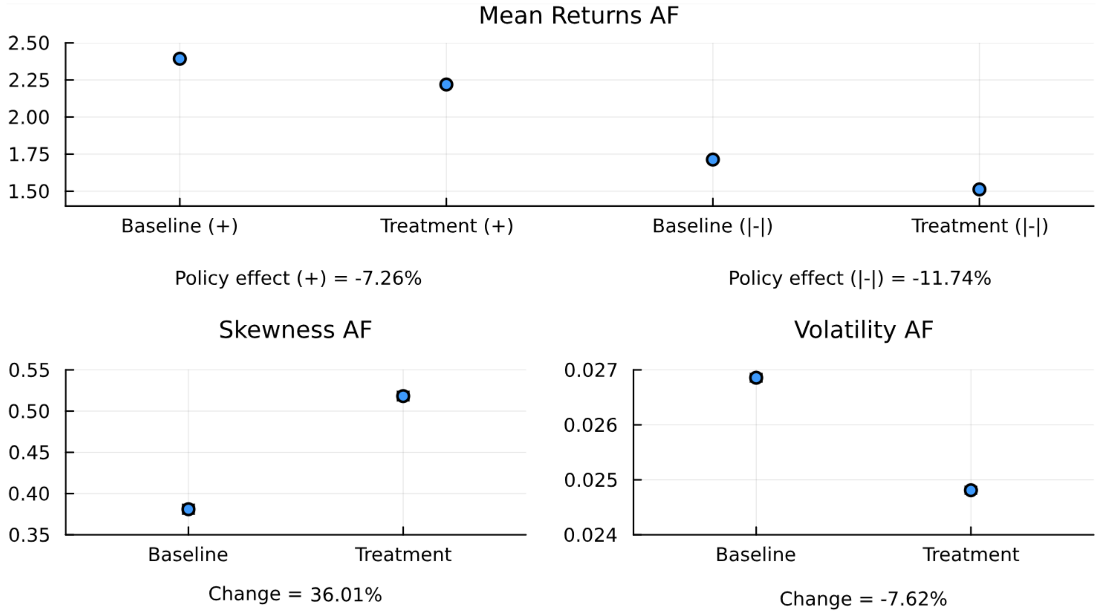


As elaborated at the beginning, the literature suggests that prices will be positively distorted. Figure 9 presents an overview of mean and maximum distortion metrics above F and unveils significant price elevations. Specifically, the mean distortion increases by 11.62 percent from 6.04 percent to 6.74 percent. Similarly, the baseline maximum registers at 10.9 percent, and the treatment maximum is at 11.71 percent, which represents a rise of 7.41 percent.

Moving on, this analysis extends to scrutinizing return patterns by distinguishing returns above and below the fundamental value. The aim is to obtain a picture of the impact of SSR on the price discovery process and, therefore, price efficiency. Recall that positive and negative movements have a corrective or distorting effect depending on whether they occur above or below the fundamental price. Negative values are depicted in absolute figures to facilitate a graphical comparison between positive and negative return values. Additionally, the skewness and volatility are provided for context. Volatility is computed as the standard deviation of the returns.

Figure 10 contains the metrics for the AF case. The returns show a skewness of 0.38 in the baseline scenario and 0.51 under SSR. This corresponds to a 36.01 percent increase. Both positive and negative returns decline in their means. The values decrease due to the SSR from 2.39 percent and 1.71 percent to 2.21 percent and 1.51 percent, by -7.26 percent and -11.74 percent for the positive and absolute negative returns, respectively. Accordingly, the volatility decreases slightly by -7.62 percent from a mean value of 0.027 to 0.025 as a result of the SSR.

Figure 10: Impact of SSR on returns metrics AF



In Figure 11, the same variables are depicted for the BF case. Here, the baseline returns show a negative skewness of -0.15. Yet, the metric flips around to a mean of 0.08 under SSR. Again, both positive and negative returns exhibit a decrease in their averages. Specifically, under SSR, the means slip from 2.11 percent and 2.27 percent to 1.96 percent and 1.92 percent, respectively, corresponding to declines of -7.29 percent and -15.46 percent. Consequently, volatility is experiencing a decline again, transitioning from a 0.029 return standard deviation to 0.026, representing a decline of 11.95 percent.

Ultimately, to address concerns about bubbles emerging and bursting after restrictions are repealed, market drift in the post-treatment control phase is examined using skewness and price level ratios. These ratios capture price level shifts from the price at the lifting of the ban to the mean and median prices in the control phase, presented in compact, standardized metrics. Additionally, comparing these ratios helps account for potential deviations from the mean.

Table 2: Market drift measures

Skewness	$P_{Median}/\ P_{Repeal}$	$P_{Mean}/\ P_{Repeal}$
0.4063	1.0038	1.0044

Figure 11: Impact of SSR on returns metrics BF

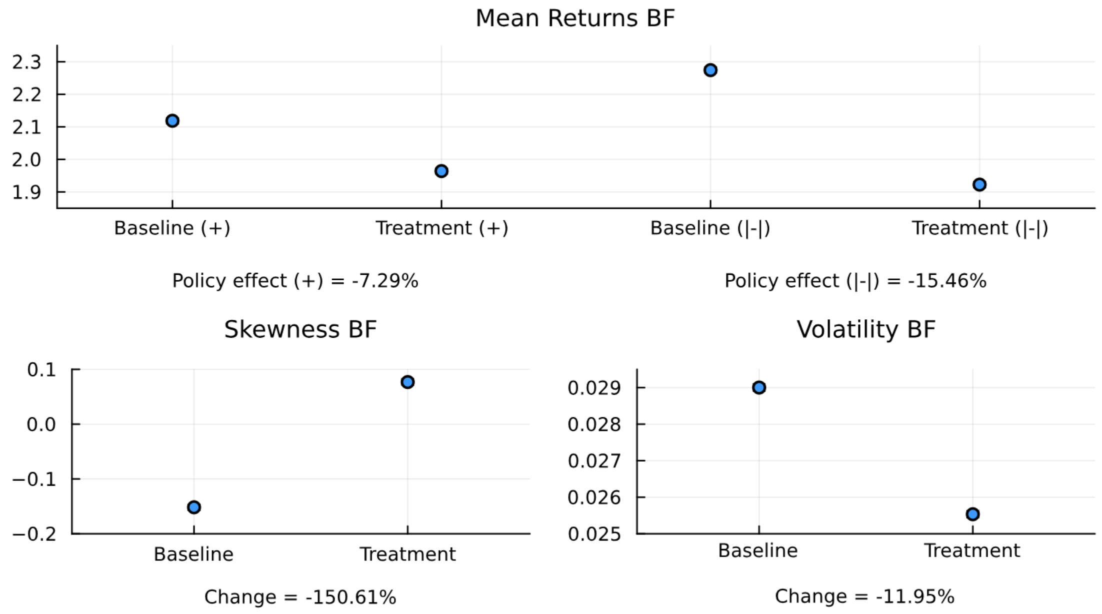


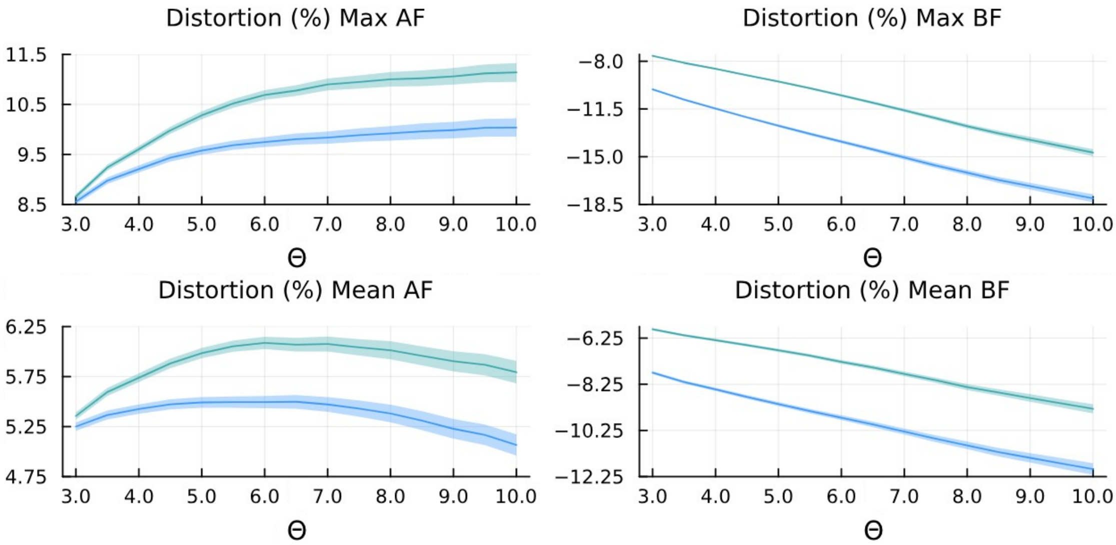
Table 2 sheds light on the repercussions of the lift of SSR on price drift ratios and skewness. After the repeal of the SSR, the mean price drift ratio and the median price drift ratio have values of 1.0038 and 1.0044, respectively. The skewness of the returns is 0.4063. Uniformly, these metrics indicate a modest positive market trend on average in the control periods.

3.3 Sensitivity analysis

To test SSR's effects of their sensitivity towards variations in the previously used policy parameter values and for the purpose of supporting prudent and effective policy design, the distortion metrics as leading indicators are subsequently computed for different values of the enactment return threshold and the ban period length. The simulation is run 5000 times for each parameter value, and the resulting mean values for the corresponding metrics are then presented as graphs, in blue for the baseline and green for the treatment case, with shaded areas around representing 95 percent confidence intervals. When examining the plots, it is essential to note that changes in insertion threshold and insertion length also lead to measurement effects. These are noticeable through changes in the baseline graphs. Changes in the policy effect are, in turn, indicated by the relationship between the treatment graphs and the baseline control graphs.

The policy threshold (Θ) refers to the question for regulators of when it is best to impose restric-

Figure 12: Enactment threshold sensitivity of SSR effects on market distortion metrics.



tions and what difference it potentially makes. Accordingly, it is varied, starting with what is commonly considered an extreme return, that is, a return value of more than twice the standard deviation of the returns, corresponding to about a 3 percent return in the model. The endpoint is set at -10 percent. This corresponds to the level at which a form of short-selling restriction is automatically triggered in the US if it materializes within one day, according to SEC Rule 201 (Securities and Exchange Commission, 2010).

Figure 12 illustrates the market distortion metrics as Θ increases. The RHS plots display the maximum and mean distortion metrics AF. In the upper chart, the maximum plot shows the baseline rising from 8.56 to 10.04 percent, while the policy treatment increases from 8.65 to around 11.14 percent. Below, the mean metrics show a slightly different picture. The baseline graph begins at 5.25 percent, initially exhibits a slight increase, and then declines to 5.07 percent. The treatment plot behaves similarly, starting at 5.36 percent. However, it shows an ultimate increase and ends at 5.79 percent. All plots exhibit a common concave shape, with the gap between the baseline and treatment widening initially and then remaining relatively constant. The RHS plots contain the graphs for the BF case. All metrics decay almost in parallel. For the maximum metrics, the baseline decreases from -10.06 percent to -18.05 percent, and the policy treatment drops from -7.61 percent to -14.7 percent. Regarding the mean metrics, the baseline falls from -7.75 percent to -11.92 percent, while the treatment declines from -5.87

percent to -9.32 percent. The gaps in both plots exhibit only a very slight widening, indicating a rather consistent policy effect.

While the economic interpretation of the results follows in the next section, at this point, a few technical notes are provided to explain the variation in the baseline plots due to measurement effects. The concave shape of the curves for the AF case may initially seem odd; however, when considered in the context of Figure 4, it is only logically consistent. Only the upward orientation of the maximum plots remains unexpected. However, this can be attributed to the fact that higher returns are more likely to occur in the high-volatility regime, with higher variability also leading to higher maximum values.

Another important consideration for policymakers is the length of measures and, accordingly, the impact beyond the short term. Thus, the goal of the following analysis is to gain insight into the medium-term effects. In technical analysis, ”medium-term” refers to a time frame spanning several weeks to several months. Hence, the sensitivity analysis varies the length from 10 to 80 periods in 15 steps. With five periods equal to one trading week, the ban length (Λ) is varied from two weeks to four months.

Figure 13: Ban duration sensitivity of SSR effects on market distortion metrics.

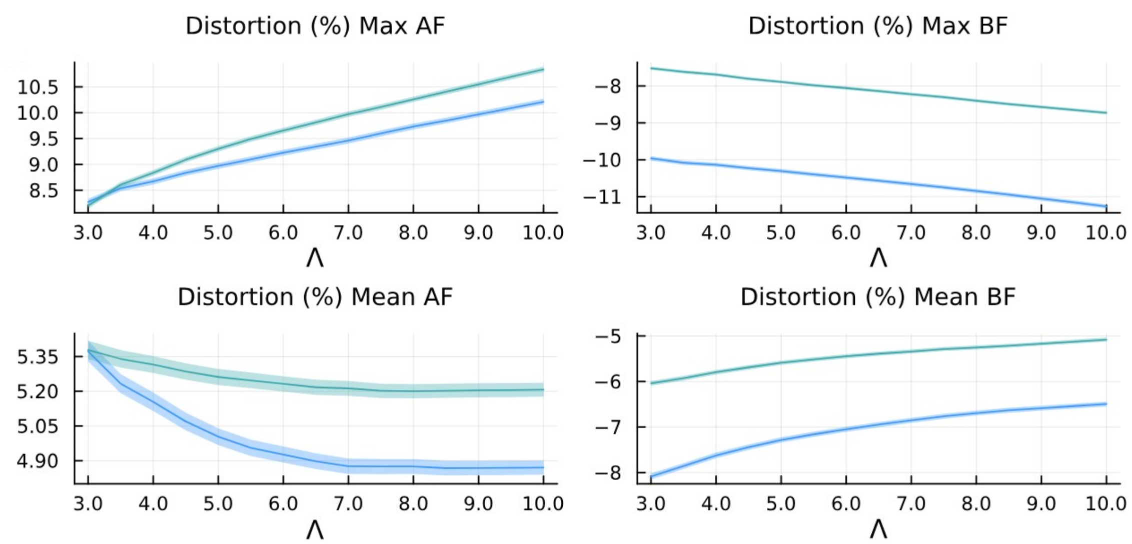


Figure 13 contains results on market distortion as Λ is increased. In the top left graph, the baseline maximum distortion AF rises from 8.27 to 10.21 percent. Under the policy treatment, it rises more, from 8.2 to 10.84 percent, indicating consistently higher distortion and an increasing

policy effect as Λ increases. Below are the graphs for the mean values AF, both of which demonstrate a convex shape. The baseline graph decays from 5.37 to 4.87 percent and then stabilizes, whereas the policy graph declines only slightly from 5.38 to 5.21. This results in an initially widening gap, which then remains steady. In the plots to the right, the distortion metrics BF are depicted. Both cases for the maximum metrics show a constant decaying trend in parallel to each other. The baseline decays from -9.96 percent to -11.26 percent. The policy treatment graph ranges from -7.52 percent to -8.73 percent. The graphs below illustrate the mean distortion values of BF. In the baseline scenario, the mean metric rises from -8.08 percent to -6.49 percent. Under the policy treatment, the mean metric similarly transitions from -6.04 to -5.08 percent. The distance between the plots stays relatively steady as Λ is varied.
Again, the conspicuous shapes, unrelated to the relationship between the scenario plots, are briefly discussed. In this instance, the mean and maximum graphs exhibit divergent trends. The trend of the maximum extreme values can be readily explained, as a longer time period allows for a greater potential to reach higher maxima. Conversely, the mean values depict the overall dynamics; thus, it is equally unsurprising that, with an extended time span, a reversion trend towards the fundamental value occurs.

4 Discussion

The findings in the previous section contain valuable implications against the background of the research question for further research and policy decisions. The results in Figure 8 indicate that the implementation of SSR leads to a decrease in distortion for maximum values and means below the fundamental value. This confirms the finding of previous works that prices are inflated when SSR are introduced. When examining the results from the perspective of price stability, it can be stated that this price increase equals a price stabilization below the fundamental value. Since the negative distortion is significantly reduced, it can be stated that SSR represent an effective tool to reduce the severity of market crashes. Additionally, the simultaneous decrease in the frequency of extreme returns and the magnitude of maximum realized returns emphasizes the fact that SSR mitigates market crash dynamics.
This can be attributed to the results in Figure 7, which indicate that SSR can curb detrimental

behavioral spirals. Under SSR, the maximum sale order sizes are uniformly reduced by roughly 20 percent. While the order sizes of swing traders are directly affected by the ban, leverage adjustments are reduced through the described channels. Specifically, restricting extrapolate sell orders leads to fewer and less strong negative price movements. This reduces the profits of chart analysis, its relative attractiveness, and, in turn, its strategy share and pull force through the herding effects. In addition, fewer sharp price falls lead to fewer high devaluations of the asset portfolio and an increase in the VaR risk measure for the bank. Both of these factors reduce the adjustment orders. Again, the result is fewer and weaker negative price movements, which underlines the stabilizing effect of SSR on the financial market. At the same time, additionally, the importance of SSR for systemic stability becomes particularly apparent, and it is therefore rightly taken into account in the policy area of macro-prudential regulation, as these network effects are contained.

This being said, the given setup is an isolated market with one representative leveraged trader, but in reality, the financial sector consists of multiple interconnected markets with multiple leveraged traders. Thus, in reality, the behavioral network effects leading to vicious selling cycles are spreading across markets. Therefore, it would be interesting to analyze the effect of SSR in agent-based models with at least two markets to control for policy externalities, as e.g. Westerhoff and Dieci (2006) do for the Tobin tax and also with more leveraged traders.

The results obtained so far align with the widely accepted view in the literature that SSR downward constrain the price discovery process. In this context, the detrimental effects on price efficiency are often emphasized. The return analysis, split into cases above and below the controlled intrinsic asset value, offers a more complete picture of the effects on efficiency.

The treatment estimates demonstrate that, in both maximum and mean terms, positive and absolute negative returns above and below the fundamental value are consistently decreased. As in both areas, volatility is tamed, the reduction in positive returns, in turn, can be comprehended as a consequence of a general calming of the market. Yet, only the net policy effect matters for the convergence to F, and in both cases, the negative price movements are more significantly affected than the positive ones. This seems to be intuitive, as these are affected by SSR. As a result, the skewness increases in both analysis areas, indicating a positive market drift.

Although this means that downward price discovery is hindered above the fundamental value, it also highlights the effectiveness of SSR in enhancing price stability and efficiency below the fundamental value. In addition, when comparing the Figure 8 and Figure 9, it becomes apparent that the supportive effect below F is stronger than the bubble effect above it. This asymmetry constitutes a novel finding and indicates that SSR lead to a net positive social benefit.

This has important implications for researchers and policymakers. For empirical analysis, it emphasizes the importance of controlling for over- and under-valuation effects when scrutinizing the repercussions of SSR, for example, using proxies as price-earnings ratios. Even though they are flawed proxies, they might help to avoid strong biases. Likewise, regulatory authorities must also consider that extreme negative price returns in overvalued markets can be healthy.

The tests of the policy for different policy parameters yield similar indications. In Figure 12, where the enactment threshold is varied, the graphs for the AF case show an initially widening and therefore strengthening policy effect. This can be linked to the policy being implemented, also already in the low volatility regime, in which there are no trends to be broken. While the conclusion of this might be to avoid precautionary pro-activism and hence distortion, the implications of the results relating to the BF case are quite the opposite. Although the plots do not show a substantial increase in the policy effect. Against the background of the accelerating nature of the behavioral spirals, the downward slope can not be understood solely due to the measurement points. Still, one can also infer that early interventions might prevent more extreme dynamics. Consequently, the appropriate policy response hinges on whether the asset is perceived as overvalued or undervalued.

In Figure 13, where the policy is applied for different durations, the AF case shows an increasing gap. This is because above F the threshold is less likely to be triggered by random incidents, rather than by systemic downward spirals. Consequently, there is less downward pressure to mitigate by the SSR, and it takes longer for the effect to unfold. Below F however, the effect is relatively constant. Another observation is that maximum metrics stray away from F and mean metrics towards it with increasing ban length. This indicates that as more time passes, increasingly extreme values are realized, but also that the market exhibits a self-recovery force, which becomes apparent in the mean.

Therefore, policy recommendations are ambivalent. There seems to be a general tendency for market recovery and no need for unnecessary friction in the market. At the same time, it can be seen that extreme scenarios are realized, which might want to be prevented. In the end, the regulatory authorities have to evaluate and decide not only about the correct valuation but also whether a downward trend is sustainably broken, or whether there is a necessity for further support of the correction, considering external market factors such as uncertainty, pessimism, and systemic stability concerns.

With this in mind, it is essential to acknowledge the hazards associated with emerging bubbles due to SSR. The results presented in Table 2 indicate that within the model, no crashes occur during the control phase after treatment. On the contrary, the skewness of the returns is positively biased, and the price level ratios also hint at an upward trend. The slight difference between the median and mean price ratios additionally suggests that price movements are likely to be relatively linear, without significant downward deviations.

As a continuation of the price trends is seen, it can be stated that the concerns about bursting bubbles are not universally applicable and should not be overestimated. Yet, all presented estimates are mean values of multiple simulations. This explicitly does not rule out the possibility that crash scenarios occurred during the simulation runs after a ban lift, and similarly, this could occur in reality. In addition, there is the possibility of excess hysteresis. As for every model of this kind, the results are subject to the Lucas critique, meaning that the reaction of agents might deviate in reality. Against this background, the risks associated with bubble formations should not be entirely neglected in policy decisions.

Another important regulatory consideration concerns risk factors such as manipulative and predatory short-selling, which are difficult to quantify. In the model, strong disturbance terms initiating downward trends may be interpreted as short or bear raid attacks, though such behavior is not explicitly modeled. Neither is the potential deterrent force that credible regulatory authorities with the competence to deploy SSR have considered. Incorporating these aspects offers another promising avenue for future research. Even if empirical studies find no preventive effect of SSR, the threat of such attacks persists, and the unquantifiable deterrent effect may create a policy prevention paradox that misleads results.

5 Conclusions

This paper examines the impact of short-selling constraints on financial stability and efficiency during times of stress. The analysis was conducted in an agent-based financial market model that explicitly controls for the fundamental value and incorporates the primary behavioral drivers of crashes, namely herding, extrapolate trades and pro-cyclical deleveraging. This framework allows a direct assessment of the stabilizing and destabilizing forces of SSR in comparison to the benchmark of the fundamental value. Three key results stand out. First, SSR are effective in mitigating severe downward distortions. This finding directly addresses regulators' primary objective of preventing crashes. Second, by distinguishing between dynamics above and below the fundamental value, the analysis reveals a novel asymmetry. While short-selling restrictions impair downward price discovery and thereby elevate prices above fundamentals, their effect below fundamentals is more pronounced: they dampen both the size and frequency of extreme negative returns and facilitate corrective adjustments back toward the fundamental value. This previously undocumented asymmetry generates a net efficiency gain in the model and offers a new contribution to the debate on the efficiency implications of short-selling restrictions. Third, the study shows that SSR weaken the propagation channels that amplify crashes. The interaction between herding dynamics and leverage adjustments is substantially dampened, leading to smaller selling orders in extreme states. In this way, SSR contribute not only to asset price stability but also to systemic stability by containing destabilizing feedback loops. Taken together, these findings suggest that SSR should be viewed as a valuable emergency tool that can deliver net social benefits by stabilizing prices below the fundamental value and mitigating systemic feedback effects in times of stress.

References

Ackert, L. F., N. Charupat, B. K. Church, and R. Deaves (2005). Bubbles in experimental asset markets: Irrational exuberance no more. *Federal Reserve Bank of Atlanta Working Paper* (2005-24).

Adrian, T. and H. S. Shin (2008). Liquidity and financial contagion. *Financial Stability Review 11*, 1–7.

Anufriev, M. and J. Tuinstra (2013). The impact of short-selling constraints on financial market stability in a heterogeneous agents model. *Journal of Economic Dynamics and Control 37*(8), 1523–1543.

Avery, C. and P. Zemsky (1998). Multidimensional uncertainty and herd behavior in financial markets. *The American Economic Review 88*(4), 724–748.

Aymanns, C. and J. D. Farmer (2015a). The dynamics of the leverage cycle. *Journal of Economic Dynamics and Control 50*, 155–179.

Aymanns, C. and J. D. Farmer (2015b). The dynamics of the leverage cycle. *Journal of Economic Dynamics and Control 50*, 155–179.

Beber, A., D. Fabbri, M. Pagano, and S. Simonelli (2020). Short-selling bans and bank stability. *The Review of Corporate Finance Studies 10*(1), 94–137.

Beber, A. and M. Pagano (2013). Short-selling bans around the world: Evidence from the 2007-09 crisis. *The Journal of Finance 68*(1), 343–381.

Bernheim, A. and M. Schneider (1935). *The Security Markets*. Ayer Company Pub.

Bessler, W. and M. Vendrasco (2021). The 2020 european short-selling ban and the effects on market quality. *Finance Research Letters 42*, 102017.

Bessler, W. and M. Vendrasco (2022). Short-selling restrictions and financial stability in Europe: Evidence from the Covid-19 crisis. *Journal of International Financial Markets, Institutions and Money 80*(3), 1–31.

Bikhchandani, S. and S. Sharma (2001). Herd behavior in financial markets. *IMF Staff Papers 47*(3), 279–310.

Boehmer, E., C. M. Jones, and X. Zhang (2013). Shackling short sellers: The 2008 shorting ban. *Review of Financial Studies 26*(6), 1363–1400.

Boulton, T. J. and M. V. Braga-Alves (2010). The skinny on the 2008 naked short-sale restrictions. *Journal of Financial Markets 13*(4), 397–421.

Bris, A., W. N. Goetzmann, and N. Zhu (2007). Efficiency and the bear: Short sales and markets around the world. *The Journal of Finance 62*(3), 1029–1079.

Brock, W. A. and C. H. Hommes (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control 22*(8-9), 1235–1274.

Brunnermeier, M. K. and M. Oehmke (2014). Predatory short selling. *Review of Finance 18*(6), 1733–1796.

Brunnermeier, M. K. and L. H. Pedersen (2005). Predatory trading. *The Journal of Finance 60*(4), 1825–1863.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Chang, E. C., J. W. Cheng, and Y. Yu (2007). Short-sales constraints and price discovery: Evidence from the Hong Kong market. *The Journal of Finance 62*(5), 2097–2121.

Cipriani, M. and A. Guarino (2005). Herd behavior in a laboratory financial market. *American Economic Review 95*(5), 1427–1443.

Day, R. H. and W. Huang (1990). Bulls, bears and market sheep. *Journal of Economic Behavior Organization 14*(3), 299–329.

Dercole, F. and D. Radi (2020). Does the ”uptick rule” stabilize the stock market? Insights from adaptive rational equilibrium dynamics. *Chaos, Solitons Fractals 130*, 109439.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics 18*(2), 277–311.

Duffie, D., N. Garleanu, and L. H. Pedersen (2002). Securities lending, shorting, and pricing. *Journal of Financial Economics 66*(2-3), 307–339.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance 25*(2), 383–417.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance 46*(5), 1575–1617.

Farmer, J. D. and J. Geanakoplos (2009). The virtues and vices of equilibrium and the future of financial economics. *Complexity 14*(3), 11–38.

Franke, R. and F. Westerhoff (2012). Structural stochastic volatility in asset pricing dynamics: Estimation and model contest. *Journal of Economic Dynamics and Control 36*(8), 1193–1211.

Geanakoplos, J. (2010). The leverage cycle. *NBER Macroeconomics Annual 24*(1), 1–65.

Geraci, M. V., T. Garbaravičius, and D. Veredas (2018). Short selling in extreme events. *Journal of Financial Stability 39*, 90–103.

Goldstein, I. and A. Guembel (2008). Manipulation and the allocational role of prices. *Review of Economic Studies 75*(1), 133–164.

Harris, L., E. Namvar, and B. Phillips (2013). Price inflation and wealth transfer during the 2008 SEC short-sale ban. *The Journal of Investment Management 11*(2), 5–28.

Harrison, J. M. and D. M. Kreps (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics 92*(2), 323–336.

Haruvy, E. and C. N. Noussair (2006). The effect of short selling on bubbles and crashes in experimental spot asset markets. *The Journal of Finance 61*(3), 1119–1157.

Hauser, F. and J. Huber (2012). Short-selling constraints as cause for price distortions: An experimental study. *Journal of International Money and Finance 31*(5), 1279–1298.

Hong, H. and J. C. Stein (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies 16*(2), 487–525.

in ’t Veld, D. (2016). Adverse effects of leverage and short-selling constraints in a financial market model with heterogeneous agents. *Journal of Economic Dynamics and Control 69*, 68–104.

Keynes, J. M. (1936). *The general theory of employment, interest, and money*. Harcourt, Brace and Company.

King, R. R., V. L. Smith, A. W. Williams, and M. Van Boening (1993). The robustness of bubbles and crashes in experimental stock markets. *Nonlinear dynamics and evolutionary economics 183*, 183–200.

Kosowski, R. and S. N. Neftci (2014). *Principles of Financial Engineering, Third Edition* (3 ed.). Academic Press Advanced Finance. Academic Press.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance 32*(4), 1151–1168.

Mitts, J. (2020). Short and distort. *The Journal of Legal Studies 49*(2), 287–334.

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys 27*(3), 670–705.

Porter, D. P. and V. L. Smith (2003). Stock market bubbles in the laboratory. *The Journal of Behavioral Finance 4*(1), 7–20.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of Political Economy 111*(6), 1183–1219.

Schinasi, G. J. (2004). Defining financial stability. Working Paper 04/187, International Monetary Fund.

Schmitt, N. and F. Westerhoff (2017). Herding behaviour and volatility clustering in financial markets. *Quantitative Finance 17*(8), 1187–1205.

Securities and Exchange Commission (2010). Risk management controls for brokers or dealers with market access. SEC Release No. 34-61595. Retrieved from https://www.sec.gov/files/rules/final/2010/34-61595.pdf.

Shiller, R. (1987). Investor behavior in the October 1987 stock market crash: Survey evidence. Working Paper 2446, National Bureau of Economic Research.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review 71*(3), 421–436.

Shiller, R. J. and J. Pound (1989). Survey evidence on diffusion of interest and information among investors. *Journal of Economic Behavior & Organization 12*(1), 47–66.

Smith, V. L., G. L. Suchanek, and A. W. Williams (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica 56*(5), 1119–1151.

Spolaore, A. and C. Le Moign (2023). Market impacts of the 2020 short selling bans. *Journal of Financial Research 46*, 1–28.

Westerhoff, F. (2008). The use of agent-based financial market models to test the effectiveness of regulatory policies. *Journal of Economics and Statistics 228*(2-3), 211–238.

Westerhoff, F. and R. Dieci (2006). The effectiveness of Keynes-Tobin transaction taxes when heterogeneous agents can trade in different markets: A behavioral finance approach. *Journal of Economic Dynamics and Control 30*(2), 293–322.

Appendix A - The banks' trading rule

This section elaborates on how the bank risk-adjusts its position as a long-term investor. For this purpose, it is worth recalling the basic ideas already presented in section 3.3. The bank strives to achieve a specific leverage ratio denoted as LR_t^{Tar} based on the scaled RiskMetrics VaR, following Aymanns and Farmer (2015a) closely.

$$LR_t^{Tar} = \Psi VaR_t = \frac{DB_t}{E_t} \tag{21}$$

Before exploring how the bank adjusts its position. All required accounting variables are properly introduced. Starting with the portfolio value, AV, held by the bank at time t, which is computed by multiplying the assets by the current market price. This is shown in the following equation:

$$AV_t = AS_t^B P_t \tag{22}$$

The asset stock, AS, of bank, B, at time, t, is determined by adding the trade order of the current period to the assets held in the previous period. The following equation expresses this:

$$AS_t^B = AS_{t-1}^B + D_t^B \tag{23}$$

On the other side of the bank's balance sheet are the equity and debt. The equity, E_t, represents its net worth and is computed by subtracting its debt from the market value of its assets. The equation is:

$$E_t = AV_t - DB_t \tag{24}$$

Given that it is presumed that the bank operates with leverage, or in other words, uses debt, viewing the account as a debt balance is more convenient. The debt balance, DB_t, is found by subtracting the current period's currency flow from the previous period's debt amount.

$$DB_t = DB_{t-1} - CF_t \tag{25}$$

The movement of funds into and out of the bank due to its transactions in the market is represented by the currency flow, CF. At the time t, the currency flow is calculated as the product of D_t^B and P_t, with a negative sign as a purchase makes money go out and vice versa.

$$CF_t = -(D_t^B P_t) \tag{26}$$

At this point, the leverage targeting, and hence the trading orders of the bank, D_t^B, move back into focus. Although the bank is aware that the price will change, following on from the assumption of the RiskMetrics approach that the returns are zero on average, the bank uses static forecasting for the price in the coming period, therefore applies $P_{t-1} = P_t^e$ as best proxy of a long term investor for short-term fluctuation. Accordingly, the bank expects:

$$LR_{t-1}^{Tar} = \frac{DB_{t-1}}{E_{t-1}} = LR_t^{Tar}$$

Note, that since equity is a function of the portfolio value and the debt amount. The bank actually aims to adjust its debt level, to meet LR_t^{Tar}. Against this background, DB_{t-1} can be understood as implied debt target, DB_{t-1}^{Tar}.

Yet, the asset price changes at the end of every period; this has two effects on the bank's account. On the one hand, does every return also affect the VaR measure and hence LR_t^{Tar} deviates. On the other hand, the price affects the portfolio value, and hence the bank's equity, E_{t-1}, changes; as a result, equation (21) no longer holds. Both effects cause the bank to deviate from its targeted leverage ratio, determined in the previous period.

$$LR_t^{Tar} \neq \frac{DB_{t-1}}{E_{t-1}}$$

Thus, the bank readjusts its position in every period. To derive the bank's trading rule, let's commence by considering the target leverage ratio. As first step, equation (21) is taken and the equations (23), (22), (24), (25) and (26) are plugged in. As D_{t+1}^B is set to readjust the portfolio correctly using static forecasting, it applies:

$$LR_t^{Tar} = \frac{DB_t}{E_t} = \frac{DB_{t-1} + (D_t \cdot P_t^e)}{(AS_{t-1} - D_t^B) \cdot P_t^e - (DB_{t-1} - D_t^B \cdot P_t^e)}$$

The goal is to isolate D in this equation to determine the number of stocks the trader should sell in order to meet their target leverage ratio.

$$D = \frac{-DB_{t-1} + LR_t^{Tar}(AS_{t-1}P_t^e - DB_{t-1})}{P_t^e}$$

Since $P_t^e = P_{t-1}$ and $(AS_{t-1} * P_{t-1} - DB_{t-1})$ equals the static equation of equity (E) at $t-1$, it can be substituted to further reduce the equation.

$$D = \frac{-DB_{t-1} + LR_t^{Tar} E_{t-1}}{P_t^e}$$

Now, to obtain an equation that allows for economic interpretation, let's rearrange this equation a bit more. Given that $LR = \frac{DB}{E}$, we can rearrange it to $DB = LR * E$. As described above, $LR_t \cdot E_{t-1}$ can be understood as the debt target DB_t^{Tar}. Accordingly, it expresses the amount of assets that have to be bought or sold to make the current debt equal to the target debt. Hence, $LR_t = LR_t^{\text{Tar}}$ under the assumption that $P_{t-1} = P_t$.

$$D_t = \frac{DB_t^{\text{Tar}} - DB_{t-1}}{P_t^e}$$

Appendix B: Stylized facts under treatment

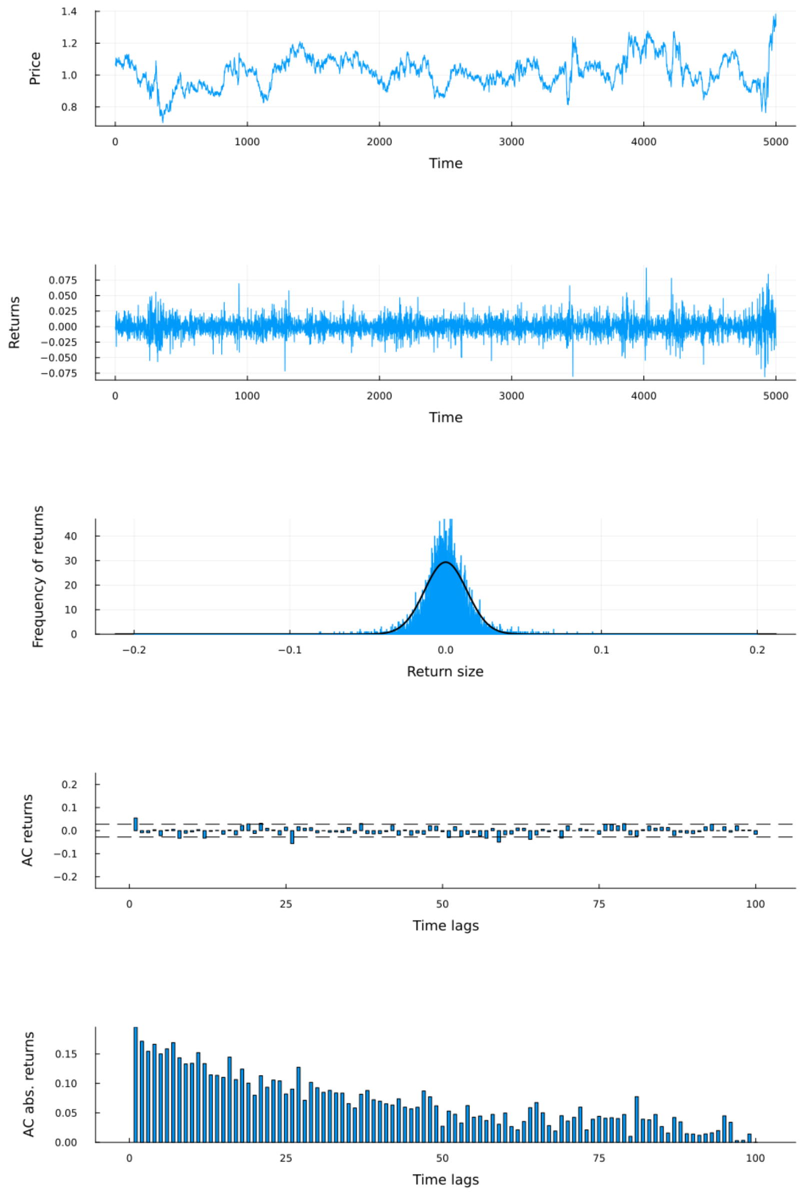


Figure 14: The illustrations above depict the stylized financial market characteristics under the regulatory regime

Appendix C: Variable design

This section provides the detailed mathematical formulations used to calculate the observational variables discussed in the main body of the paper. There the presented metrics are compared as means across numerous repetitions. However, this section focuses solely on the formulas illustrating the method for computing values obtained from a single simulation run to ensure transparency and reproducibility.

Let's recall that the relevant variables are tracked throughout the observatory phases. The number of these subsets is denoted by J and indexed by j. Observations within each subset are indexed by t and the length of each observatory phase is represented by T. However, for metrics such as skewness and standard deviation, calculations are based on the aggregated values from all sub-samples. This approach is necessary because individual sub-samples are too small, making estimates potentially unreliable and heavily influenced by outliers.

5.0.1 Distortion Analysis

The distortion metrics for mean and maximum values above and below the fundamental value are all based on the computation of the price bias in every single period. This is given with the percentage deviation of the price to the fundamental value:

$$\Delta_t = \left(\frac{P_t - F}{F} \right) \times 100$$

Let the subsets of the observatory periods be denoted by Δ_{sub} and the subsets filtered for positive distortion above the F and negative distortion below F as Δ^+_{sub} and Δ^-_{sub}, respectively. The corresponding set of these samples for an entire simulation run is given by Δ^+_{run} and Δ^-_{run}

$$\Delta^+_{sub} = \{\Delta_t \in \Delta_{sub} \mid \Delta_t > 0\}, \quad \Delta^+_{run} = \{\Delta^+_{\text{sub}_j}\}_{j=1}^{J}$$

$$\Delta^-_{sub} = \{\Delta_t \in \Delta_{sub} \mid \Delta_t < 0\}, \quad \Delta^-_{run} = \{\Delta^-_{\text{sub}_j}\}_{j=1}^{J}$$

Accordingly, the formulas for the mean and maximum distortion above the F, as well as the mean and minimum distortions below the fundamental value, are as follows:

$$\text{Mean distortion (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T}\Delta_t(\Delta_t > 0)$$

$$\text{Maximum distortion (AF):} = \frac{1}{J}\sum_{j=1}^{J}\max(\Delta^{+}_{\text{sub}_j})$$

$$\text{Mean distortion (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T}\Delta_t(\Delta_t > 0)$$

$$\text{Maximum distortion (BF):} = \frac{1}{J}\sum_{j=1}^{J}\min(\Delta^{-}_{\text{sub}_j})$$

5.0.2 Price level ratios

Transitioning to the price level ratios, let's recall that for all three fractions a metric (exit price, mean and median) is set in relation to the entry price. That is the first price of an observation period. The price samples of these phases are given by Π_{sub} and the collective set of sub-samples of an entire simulation run by Π_{run}.

$$\Pi_{sub} = \{P_t\}_{t=1}^{T}, \quad \Pi_{run} = \{\Pi_{sub}\}_{j=1}^{J}$$

This being said, the price level ratios are computed as follows:

$$\text{Entry/Exit Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{P_T}{P_1}$$

$$\text{Entry/Mean Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{\frac{1}{T}\sum_{t=1}^{T}P_t}{P_1}$$

To calculate the median of the sub-samples ($\widetilde{\Pi}_{\text{sub}}$), the elements within each sub-sample are arranged in ascending order, thereby altering their respective indices. Let P_i denote the elements organized in ascending order such that $P_1 < P_2 < \ldots < P_N$, where N represents the length of the samples and their highest element. Accordingly, the middle positions of the series are given by n=N/2 and m=(N/2)+1.

$$\widetilde{\Pi}_{\text{sub}} = \begin{cases} P_m & \text{for odd } N \\ \frac{P_n+P_m}{2} & \text{for even } N \end{cases}$$

$$\text{Entry/Median Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{\widetilde{\Pi}_{\text{sub, j}}}{P_1}$$

5.0.3 Return Analysis

Returns are computed in each period as a percentage change from P_{t-1} to P_t.

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

The return analysis covers mean negative and positive returns as well as the skewness and volatility above and below the fundamental value. The samples for negative and positive returns above and below the fundamental value are given by:

$$R_{\text{sub}} = \{r_t\}_{t=1}^{T}, \quad R_{\text{run}} = \{R_{\text{sub}_j}\}_{j=1}^{J}$$

$$\text{Mean positive returns (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} r_t(r_t > 0 \wedge P_t > F)$$

$$\text{Mean positive returns (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} r_t(r_t > 0 \wedge P_t < F)$$

$$\text{Mean absolute negative returns (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} |r_t|(r_t < 0 \wedge P_t > F)$$

$$\text{Mean absolute negative returns (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} |r_t|(r_t > 0 \wedge P_t < F)$$

Let's recall the crash pattern variable set, encompassing the simulation means of the maximum negative return, an occurrence rate for extreme returns denoted as χ_{count}

$$\text{Maximum absolute negative return:} = \frac{1}{J}\sum_{j=1}^{J} |\min(R_{\text{sub}_j}|)$$

$$\chi_{\text{count}} = \frac{1}{J}\sum_{j=1}^{J}\left(\frac{100}{T}\right)\sum_{t=1}^{T} 1(r_t < \theta)$$

As previously articulated, the skewness and volatility are computed using the united sample that incorporates all individual sub-samples.

$$R_{sub}^{AF} = \{r_t \in R_{sub} \mid P_t > F\}, \quad R_{run}^{+,AF} = \bigcup_{j=1}^{J}\{R_{sub}^{+,AF}\}$$

$$R_{sub}^{BF} = \{r_t \in R_{sub} \mid P_t < F\}, \quad R_{run}^{+,AF} = \bigcup_{j=1}^{J}\{R_{sub}^{+,AF}\}$$

This being said, for the skewness of the control phases after the bans is n represented it si not distinguished between above or below F, this sample is given by R_{sub}.

$$R_{\text{sub}} = \{r_t\}_{t=1}^{T}, \quad R_{\text{run}} = \bigcup_{j=1}^{J} R_{\text{sub}_j}$$

The skewness follows the standard calculation. The symbol s stands for the standard deviation of the return series.

$$\text{Skewness} = \frac{J}{(J-1)(J-2)}\sum_{j=1}^{J}\left(\frac{r_j - \bar{r}}{s}\right)^3$$

$$\text{Volatility} = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}(r_j - \bar{r})^2}$$

5.0.4 Crash Dynamics Analysis

To track the effects of herding toward extrapolate behavior, the sell order sizes by the bank and swing traders using chart analysis are collected if chart analysis was the dominant strategy in the previous period and the collective order size of traders using it was negative. The aggregated orders by swing traders using chart analysis is given by:

$$D_t^{CA} = \sum_{i=1}^{N} D_t^i \cdot (I_t^i = CA)$$

Building upon this, the samples for variable HE→E are given by EE_{sub} and EE_{run} as well as for HE→L by EL_{sub} and EL_{run}.

$$EE_{sub} = \{D_t^{CA} \mid D_{t-1}^{CA} < 0 \wedge H_{t-1}^{CA} > H_{t-1}^{FA}\}, \quad EE_{run} = \{EE_{\text{sub}_j}\}_{j=1}^{J}$$

$$EL_{sub} = \{D_t^{B} \mid D_{t-1}^{CA} < 0 \wedge H_{t-1}^{CA} > H_{t-1}^{FA}\}, \quad EL_{run} = \{EL_{\text{sub}_j}\}_{j=1}^{J}$$

Likewise, the effect of the leverage adjustment sell orders is measured using both trade order sizes, if the leverage adjustment order was negative in the previous period. The sub-samples for variable L→E is given by LE_{sub} as well as for L→L by LL_{sub}. The sets for the entire runs are given by LE_{run} and LL_{run} respectively.

$$LE_{sub} = \{D_t^{CA} \mid D_{t-1}^{B} < 0\}, \quad LE_{run} = \{LE_{\text{sub}_j}\}_{j=1}^{J}$$

$$LL_{sub} = \{D_t^{B} \mid D_{t-1}^{B} < 0\}, \quad LL_{run} = \{LL_{\text{sub}_j}\}_{j=1}^{J}$$

Pursuant to this, the estimates are given.

$$\text{HE}{\to}\text{E} = \frac{1}{J}\sum_{j=1}^{J}\min(EE_{\text{sub, j}})$$

$$\text{HE}{\to}\text{L} = \frac{1}{J}\sum_{j=1}^{J}\min(EL_{\text{sub, j}})$$

$$\text{L}{\to}\text{E} = \frac{1}{J}\sum_{j=1}^{J}\min(LE_{\text{sub, j}})$$

$$\text{L}{\to}\text{L} = \frac{1}{J}\sum_{j=1}^{J}\min(LL_{\text{sub, j}})$$

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