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an Agent-Based Model Perspective**

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**Subjective Well-Being of Corporate Managers And Its Impact on Stock Market
Volatility and Financial Stability During the Covid-19 Pandemic in Poland:
Agent-Based Model Perspective**

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Abstract

This study aims at connecting the behavioral corporate finance (micro level) perspective and complexity theory along with agent-based modelling in order to analyze the impact of selected behavioral managerial factors on aggregated data related to the financial market stability (macro level). Specifically, we want to explore whether subjective well-being (SWB) of corporate managers (CEOs) impacted their business decisions during the Covid-19 pandemic, and how it may be related to volatility of stock prices and the issue of financial stability during this critical period. Our study is based on a survey of 255 managers of companies listed on the Warsaw Stock Exchange in Poland over the period Using the results of this survey, we build an agent-based model (ABM) calibrated for the specific case of Poland to investigate how decision making of CEOs, stemming from their SWB, influence the stock prices and selected financial market dynamics indicators. The results of our study indicate that the excess volatility of stock prices may be a function of changes of SWB of managers, which in turn could lead to some crashes on the macro level with respect to financial stability.

Key words: subjective well-being; CEO; Covid-19; agent-based model.

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Introduction

Decades of studies in behavioral economics proved the need for incorporating psychological insights for better understanding of many research topics in neoclassical economics (e.g. Kahneman & Tversky, 1979; Akerlof & Schiller, 2009; Kahneman, 2012;). One of such area deals with the bounded rationality of investors and existence of so called stock market anomalies, which formed the field of behavioral finance (e.g. De Bondt & Thaler, 1987; Thaler, 2005, 2015). Extensive studies of behavioral finance proponents provided the real picture of stock market investor and the market at the aggregated level, which countered the classic finance paradigm based on the expected utility theory (Von Neumann and Morgenstern, 1944) and efficient market hypothesis (Fama, 1970). Despite this impressive empirical strain, still several research gaps within behavioral finance school remained to be filled in. One of them is the area of behavioral corporate finance, which concentrates on the bounded rationality of corporate managers and its relationship with the quality of company management (Baker & Wurgler, 2013; Malmendier et al., 2011; Szyszka, 2013). Several authors observed how various behavioral biases are linked to the bounded rationality of chief executive officers (CEOs), which, in turn, may obstruct specific managerial decisions (e.g. Boulton & Campbell, 2016; Rzesutek & Szyszka, 2020). However, previous studies from that or similar areas in behavioral finance were usually poor in providing convincing psychological rationale for explaining irrational behaviors of investors, managers or other business entities (Kushwaha et al., 2023; Sahi, 2017). In other words, although they relied on selective psychological terms (e.g. heuristics), but often

without thorough analysis of psychological theories underlying them with respect to its application to economic behavior, which came under criticism of being atheoretical. In our study, we focused on the role of subjective well-being (SWB) of the Polish CEOs during the Covid-19 pandemic in the context of their various business decisions during this critical period in their companies.

One of the most significant theoretical model of well-being in psychology is the tripartite model of subjective well-being (SWB; Diener et al., 1985, 2016). According to this model, SWB is defined as people's satisfaction with their lives as a whole or with particular domains of their lives and consists of two main elements: satisfaction with life, which is the cognitive aspect of subjective well-being (CWB) and affective well-being (AWB), i.e., positive and negative emotional reactions to peoples' life. Dozens of studies showed that high levels of SWB are related to good physical health, personal happiness, and optimal psychosocial functioning in various area of life, starting from intimate relationships to work environment (see for reviews e.g. Diener et al., 2016; Fredrikson, 2013; Steptoe et al., 2015). Although SWB was found to be relatively stable over time, it was also observed that some critical life events (e.g. divorce, loosing job, retirement), can have negative impact on SWB, yet they had much powerful and persistent influence on CWB components in comparison to aforementioned AWB elements (Luhman et al., 2012). Sometimes such critical event can take a form of global and unexpected phenomena for the majority or even the whole the population in the world, which was the case of the Covid-19 pandemic.

The Covid-19 pandemic was associated with sharp economic recession and serious turbulences in financial markets all over the world (e.g. Li et al., 2022; Sharif et al., 2020; Su et al., 2021). As far as the company management, pandemic crisis was linked to high level of uncertainty in business activity and great challenges for companies' management due to numerous totally uncontrollable factors, like significant supply chain disruptions, inflationary pressures, banks' tightening lending policies towards consumers and firms and the constant

uncertainty and fear about spread of the coronavirus, which resulted in numerous limitations in social life activity (e.g. Bairoliya & Imrohoroglu, 2020; Kushwaha et al., 2023). One unique aspect of the Covid-19 crisis, which made it particularly stressful for CEOs was the fact that it was based on the non-economic, health factors, so the traditional tools of economic stimulation against the financial crises occurred to be powerless to a great extent (Sharma et al. 2020). All these global stressors may have undisputable negative impact on SWB and economic decisions among various business entities (Kushwaha et al., 2023), including CEOs (Rzeszutek et al., 2023). However, to our best knowledge, there was no study to examine the potential interconnection between managerial SWB with regard to company management from the micro level and particular macroeconomic dynamics in the form of financial stability during pandemic. To perform such task so, we used the results of Rzeszutek et al. (2023) survey on SWB of Polish CEO's during pandemic with respect to corporate management practices in risk management and investment policy during the Covid-19 pandemic. Our goal was to include these results from micro level into a macroeconomic Agent-Based Model (ABM) calibrated for selected financial macroeconomic indicators in Poland. In our study we propose two main hypothesis: 1) subjective well-being (SWB) of corporate managers (CEOs) impacts their business decisions (micro level); 2) managerial decisions stemming from managers' SWB might impact stock prices volatility and influence stability of financial markets on an aggregated level (macro level).

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Agent Based Modeling theoretical framework

In the following section we will introduce a theoretical framework of agent based modeling in order to capture the impact that subjective wellbeing of CEO's could have on the individual decision making of traders. The aim will in turn be to explore how such influence

could impact financial markets, in particular both the short and the long time price stability of markets.

ABM is a relatively new simulation tool that is starting to be increasingly used by behavioral economics proponents, as it may provide the missing association between micro and macro behavior of various economic agents, which till now was lacking in research methodology of behavioral economics (see, e.g., Andersen & Nowak, 2013; Caverzasi, & Godin, 2013; LeBaron, 2006; Rekik et al., 2014). More specifically, ABM main assumption on existence heterogeneous, bounded rational agents, which mutual interaction and their aggregation at the micro level may generate unexpected structures at the macro level (Le Baron, 2006) reflects the core idea hidden in many behavioral models of the financial markets (Thaler, 2015), yet for many years never empirically tested due to lack of appropriate data analysis tools. However, the use of ABM in corporate behavioral finance is still rare with only two studies known by us (Rzeszutek et al., 2020, 2021). Historically, the interest in ABMs to describe financial markets were due to the fact that they could be used to reproduce quantitative empirical statistical properties of real markets, like the autocorrelation of price returns, the autocorrelation of volatility, and the marginal distribution of price changes (Lux 1998; Lux & Marchesi 1999; Levy, Levy & Solomon 2000). The common feature of these models were bounded rational agents that are chartists, using past price behavior to predict future prices, and rational expectation agents, using a fundamental price in their guide as how to trade. The initial wave of interest in such models, were since they in contrast to analytical models were able to show how bounded rationality could be understood as the root behind real empirical price changes and volatility. In the following we will introduce another ABM, but with the difference that the RE agents not only use the price itself in their decision making to trade, but also the *uncertainty* of the price. We then link the uncertainty of the price to the SWB. To our knowledge such a feature has never been used in ABMs describing financial markets, and as will be shown, such a feature is essential in order to understand volatility fluctuations in market conditions with high uncertainty.

We describe price formation in financial markets in terms of two types of different traders, corresponding to agents that are i) speculative agents who use the information of past price moves in order to try to predict the next future price movement, and ii) agents that use rational expectations in order to determine the fundamental price of an asset.

i) *Speculative agents*: are introduced via the so-called “\$-Game” (“\$G”) [1], in which single agents make their investment decisions based on past price behavior with the objective to maximize their profit payoff function. We can also imagine those agents as technical investors (chartists) who neglect fundamental information and focus predominantly on signals generated by prior formation of prices. The basic \$G scheme consists in a repeated game where the players choose one out of two alternatives (buy or sell) at each time step based on past price information. The mathematical definition of the model includes N agents that simultaneously trade in a one-asset financial market over a time horizon of T periods. At each t period, with $t < T$, each agent i chooses the best performing strategy at time t , $S_i^*(t)$ among S_i different strategies that are assigned at the beginning of the game. The “*” notation is used to indicate the “best” strategy, which will be defined in the following. It is important to note the time behavior t in the notation $S_i^*(t)$ since as the market dynamics change over time, so will the best strategy change as a function of time, which in turn change the market, leading to important feedback loops. We will denote the action of the j 'th strategy of agent i at time t for $a_i^j(t)$. In the \$G strategies use the last M price directions in order to predict the next price move. If e.g. $M = 3$, and the last M directions were (0,0,1) – meaning that the last price movement was up, and the two price movements before that were down - then a strategy conditioned on that price pattern will predict whether to buy ($a_i^j(t) = 1$), or sell ($a_i^j(t) = -1$). Since for a fixed M , there are 2^M different price histories, a strategy in the \$G is a table of size 2^M , recommending for each price history whether to buy or to sell. This means that the total number of \$G strategies goes like 2^{2^M} , an

astronomical large number even for relatively small M , which illustrates the complexity of the game.

We will call the payoff function of the i 'th agents j 'th strategy for $G_i^j(t)$. Agents in the $\$G$ use their strategies in order to try to predict and profit from the next price move. If e.g. the j 'th strategy that agent i uses at time $t - 2$, $a_i^j(t - 2)$, issue a market buy order, then the market maker will collect that buy order and deliver it to the agent at a price $p(t - 1)$. It is however not until we know what happens next (did the price increase or decrease between from $t - 1$ and t ?) that we can say whether the action issued of strategy $a_i^j(t - 2)$ was profitable or not. The change in the payoff function of the i 'th agent's j 'th strategy is therefore assumed to be:

$$\Delta G_i^j(t) = a_i^j(t - 2) R(t) \quad (1)$$

with $R(t) = \ln\left(\frac{p(t)}{p(t-1)}\right)$ the return of the market between time $t - 1$ and t . In our ABM the return is assumed to be determined by the action of all the agents $A(t)$ (speculative and RE agents) divided by the liquidity λ :

$$\Delta G_i^j(t) = a_i^j(t - 2) \frac{A(t-1)}{\lambda} \quad (2)$$

In a game with $\$G$ agents only, the cumulative action is given by $A(t) = \sum_{i=1}^N a_i^*(t)$. The “*” notation is an indication that at each time step t each agent uses it's best strategy out of the S possible strategies, meaning the strategy which has the largest cumulative return at that time step. So for an ABM with only with $\$G$ agents

$$\Delta G_i^j(t) = a_i^j(t - 2) \sum_{i=1}^N a_i^*(t - 1) \quad (3)$$

ii) *Rational Expectation (RE) agents*: are the agents that are rational in their way of trying to assess what is the fundamental right price of an asset based on available information set. In other words we can also call them fundamental traders. In our ABM we will assume a certain percentage ρ are RE agents, and the remaining $1 - \rho$ are speculative agents. The RE agents are

rational in the sense that when each agent try to estimate what should be the fundamental price p_F , they might not find the exact right price, but averaging over the estimate of all of the RE agents, gives the right price p_F , meaning there is no consistent bias in the decision making of the RE agents. This is in line with Fama's (1965) understanding of the relation between the fundamental value and the market price. Market price does not have to be equal to the fundamental value (which often in the real world with a lot of ambiguity is not really known) but it is the best approximation of the fundamental value and there is equal probability at each given moment of time that a stock is overvalued or undervalued. RE agents are heterogenous and their perception of the current market price versus the fundamental value differs.

Specifically, with Pr_F we will denote the probability a given RE agent thinks that the current price $p(t)$ is the right fundamental price p_F . We assume that Pr_F is given by:

$$Pr_F = e^{-\gamma^2}; \gamma = \frac{p(t)-p_F}{X} \quad (4)$$

An agent will therefore think that the current price is not the right fundamental price with the probability Pr_{NF} :

$$Pr_{NF} = 1 - Pr_F \quad (5)$$

The factor X in the denominator of γ is our new contribution trying to probe how subjective wellbeing of CEOs on a microscopic level can influence market price formation on a macroscopic level. Ultimately prices in a market are given by the decision making of the traders acting in this given market. The traders however watch the decision making of the CEOs and that shapes their expectations of the proper fundamental price, AND, as we now postulate, the uncertainty X of the fundamental price. If there's lot of uncertainty (say due to erratic behavior of the CEO, think e.g. former Twitter and Elon Musk) it simply means that traders now have a much larger *range* of prices they believe should be the right fundamental price. Note that when you take the expectation value of the beliefs of traders you still get the right fundamental price p_F (there is no bias creating erratic prices). This is also the case in our new version of rational

expectations, however what is new, as will be shown, is that the larger the price range in the expectations of the traders, the larger the volatility of the market. This is something NOT described in traditional rational expectations theory.

The action of the RE agents are now determined as follows. If a RE agent determines (with probability Pr_F) that the current price $p(t)$ is the right fundamental price P_F , that agent takes no action. If not (probability Pr_{NF}) the agent thinks that the price is overvalued (case $p(t) > p_F$) and will sell, or undervalued (case $p(t) < p_F$) in which case the agent instead will buy the asset.

Results

In fig. 1 we show some of the price trajectories that occur in our ABM where a certain percentage ρ of RE agents and a percentage $1 - \rho$ of $\$G$ agents. ***** see e.g. some of the price versus time figs. that Szymon send you. We should decide on some few (4) illustrative figures. We should comment on the figs + parameters used. *****

Insert Figure 1 around here

Figure 1: Examples of price time series. *The 4 different plots show some illustrative price time series of our ABM. The parameters used were $N=1001$, $T=1000$, $\rho=0.75$, $\lambda = 500N$, $M=10$, $S=5$. The plot in a) corresponds to $X=0.1$, b) $X=1$, c) $X=10$, and d) $X=100$.*

As one can see there appears to be the tendency that for a given fixed ρ the larger the X factor, the larger the volatility of the market.

We can now quantify this observation by looking at the quantiles initiating $K=10000$ different ABM market simulations, each done over $T=100000$ time periods. In fig 2 we show for each time period t the 99%, and 1% quantile of those simulations, meaning that only 100 runs at that

time t would have price behavior above the indicated (grey circles) 99% quantile, and similarly only 100 runs would go below the 1% quantile (grey circles).

Insert Figure 2 around here

Figure 2: Impact of X factor on the price range. *Each plot shows as a function of time, 99% price quantile (upper grey circles), 50% price quantile (middle grey circles), and, 1% price quantile (middle grey circles). The parameters used were $N=1001$, $T=10000$, $\lambda = 500N$, $M=10$, and $S=5$. Each column correspond to simulations done with a fixed value of $\rho=0.55, 0.75, 0.95$ and the different rows correspond to different values of X , going from top to bottom: $X=0.1, 1, 10$, and 100 . Thin red lines illustrates the solutions of Eq.(7) showing in general a nice agreement between the theoretically predicted price range and the price range found in our ABM simulations .*

The price range of the market can now be calculated by observing that the range of speculative price behavior will attain its maximum/minimum at the precise moment when there will be more RE agents taking action compared to the number of \$G agents taking a unified action (all want to buy or sell). If one call the price range $\Delta \equiv p^{max/min}(t) - p_F$ with $p^{max/min}$ the maximum (minimum) observable price value, then Δ can be determine by estimating for which value of Δ it is more likely that a RE agent takes action compared to a \$G agent taking (assumed unified) action. The probability that a RE agents takes action, is the compounded probability that an agent is a RE agent times the probability that the agent takes an action. This is the l.h.s. of Eq.6. Since unified action is assumed among the \$G agents, the probability that an action of a \$G agent is opposite to a RE agent is given by the r.h.s. of Eq. 6. Solving for Δ one obtain Eq.7.

$$(1 - e^{-\gamma_*^2}) \rho > (1 - \rho); \gamma_* \equiv \frac{\Delta}{X} \quad (6)$$

$$\Delta = \mp \sqrt{-\ln(2 - \frac{1}{\rho})} X \quad ; \quad 0.5 < \rho < 1 \quad (7)$$

As can be seen from fig 2 we can see that the price range via the quantiles indeed follows Eq. 7 (red lines) thereby showing how a microscopic uncertainty can have macroscopic consequences.

It should finally be noted that to in order to test our assumptions and framework we have so far only studied the case where X and P_F were constant, and have in that case been able to get results in steady state. According to rational expectations, new information influences P_F that changes over time. We now postulate that information not only impacts P_F but also X so a proper study within the framework of rational expectations will require a dual study of the time dependence of both variables.

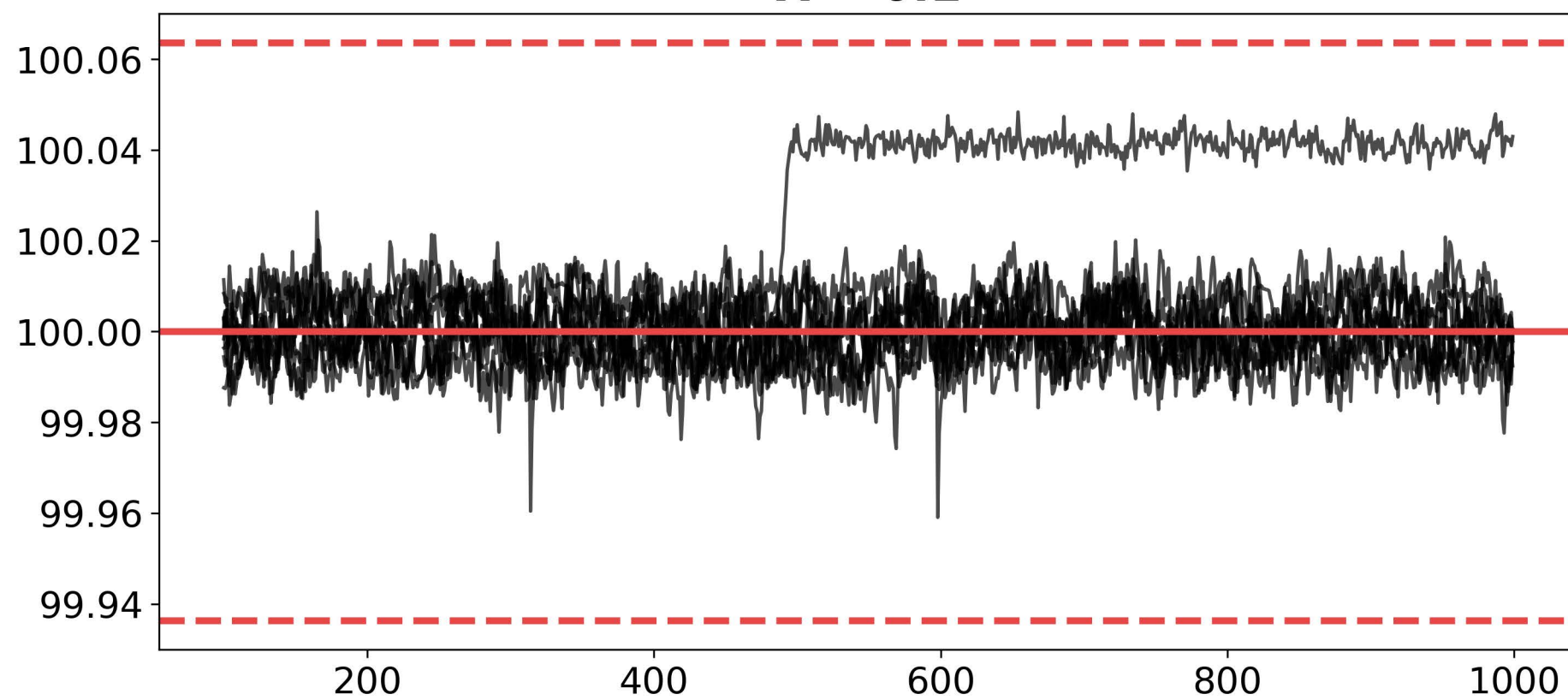
Discussion...

We have introduced a new ABM in order to capture the impact which changes in SWB of CEOs could impose on the stream of information perceived by traders in a financial market. Our claim is that the *uncertainty* about the decision making of CEOs could directly transpose into an uncertainty of traders how to position themselves in the markets, and this we have shown via ABM can lead to long term price instability of the markets. We have been able to quantify, via a formula, the size of price instability which fits nicely with what is obtained in the ABM simulations.

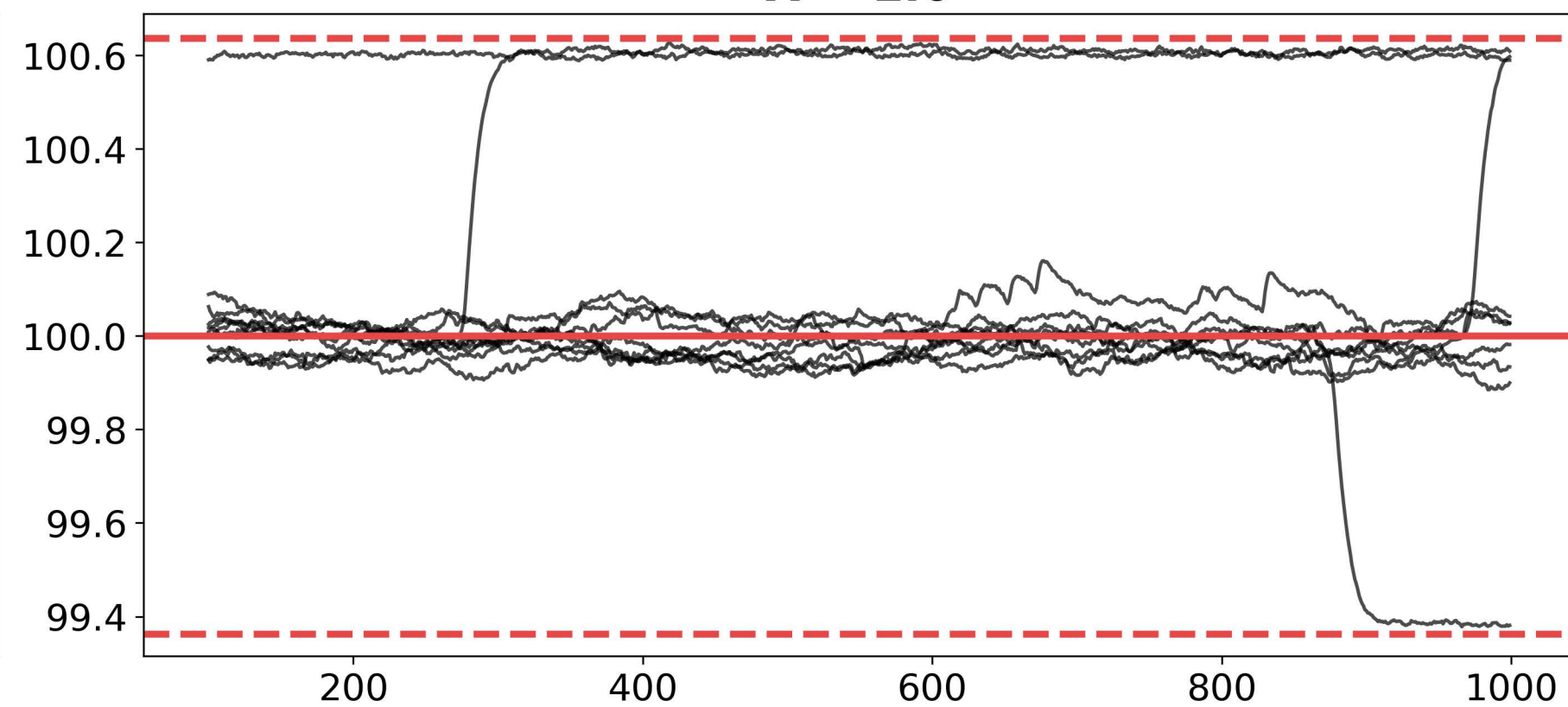
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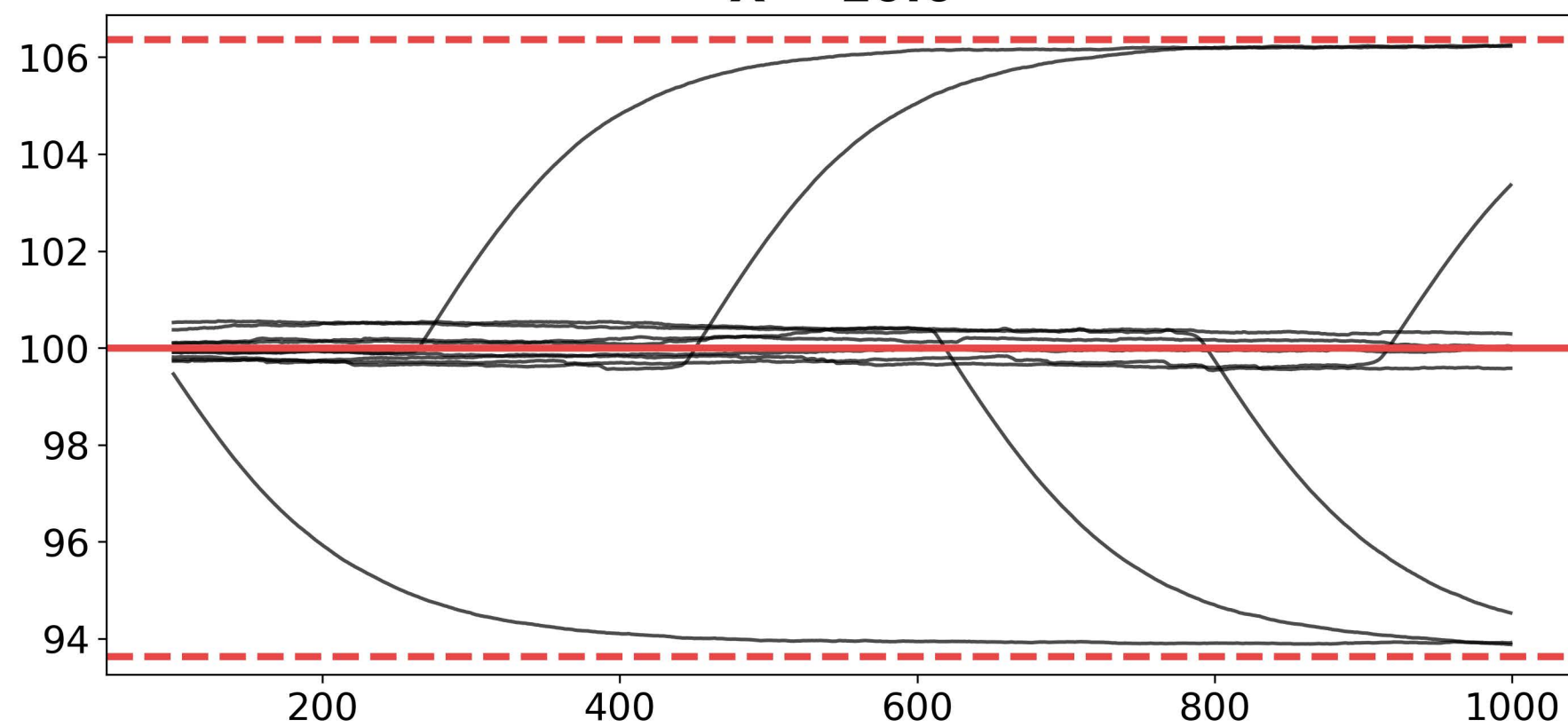
X = 0.1



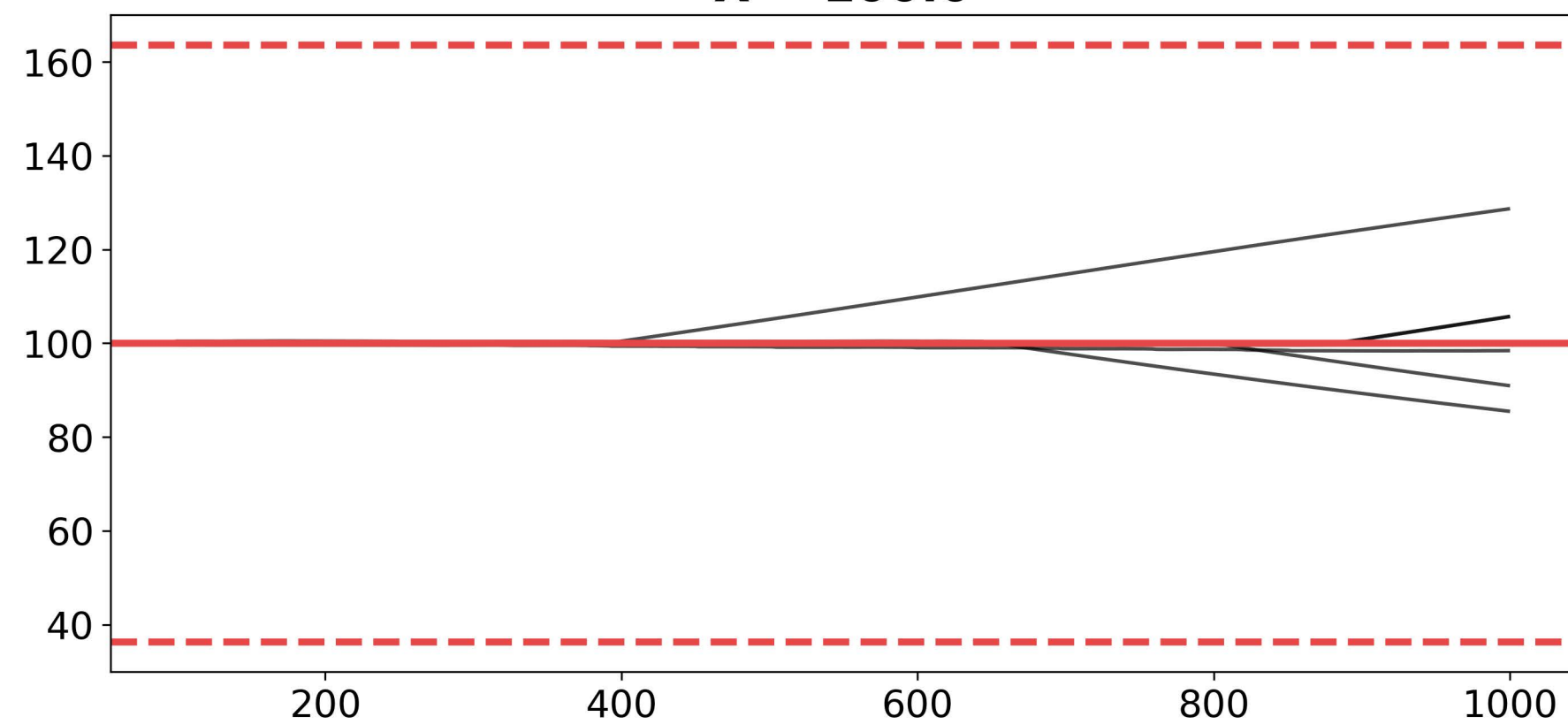
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X = 10.0

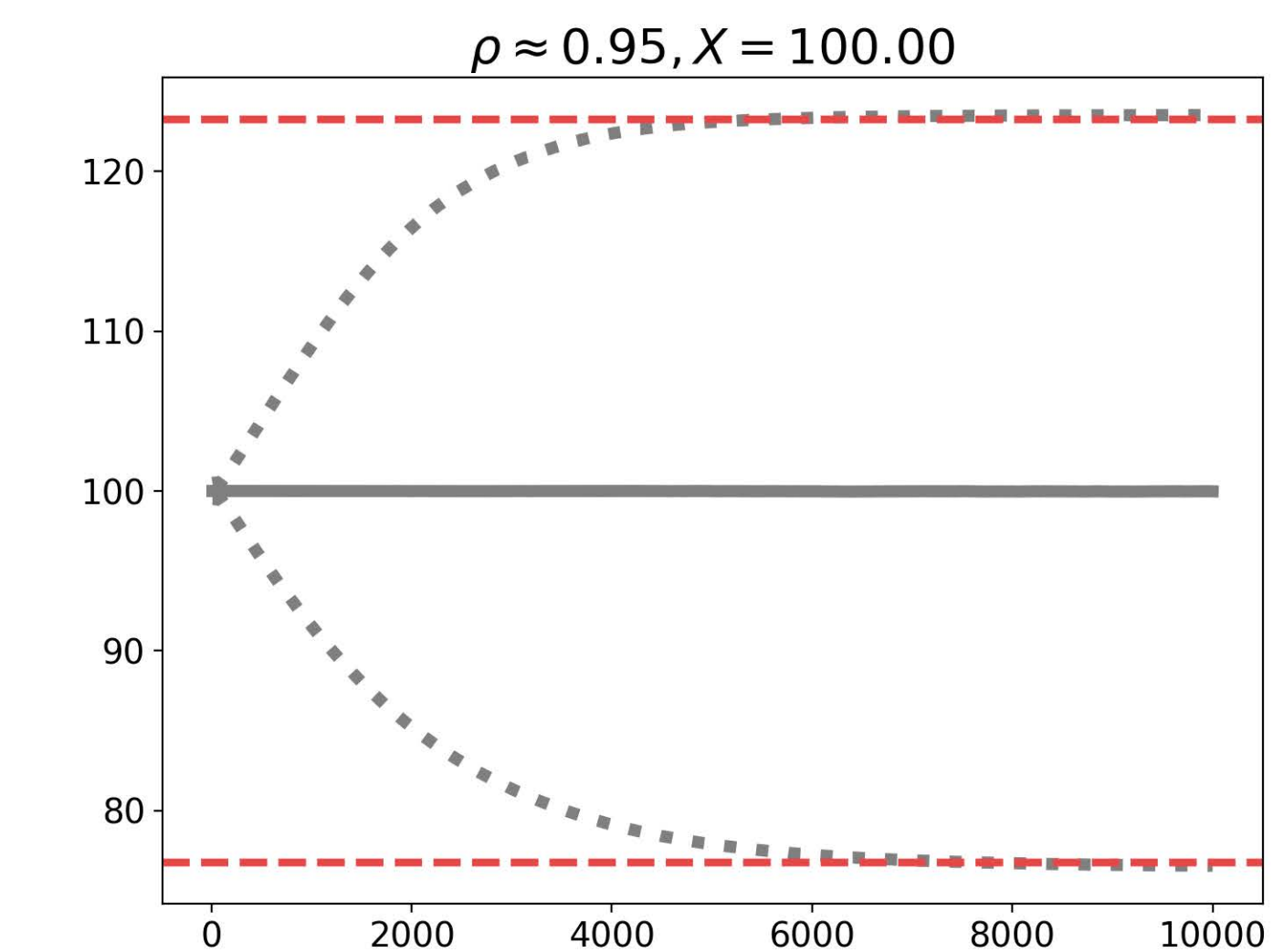
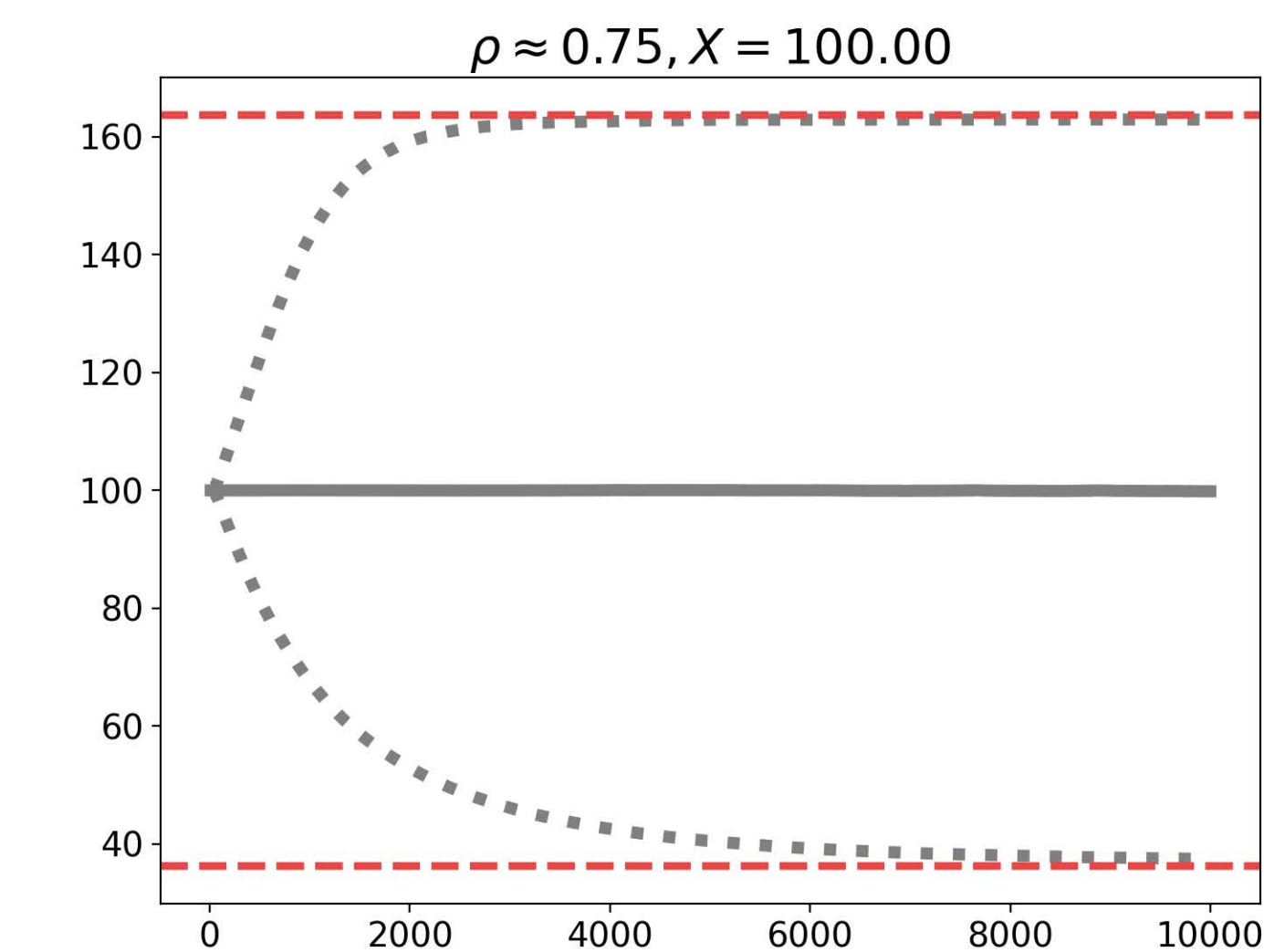
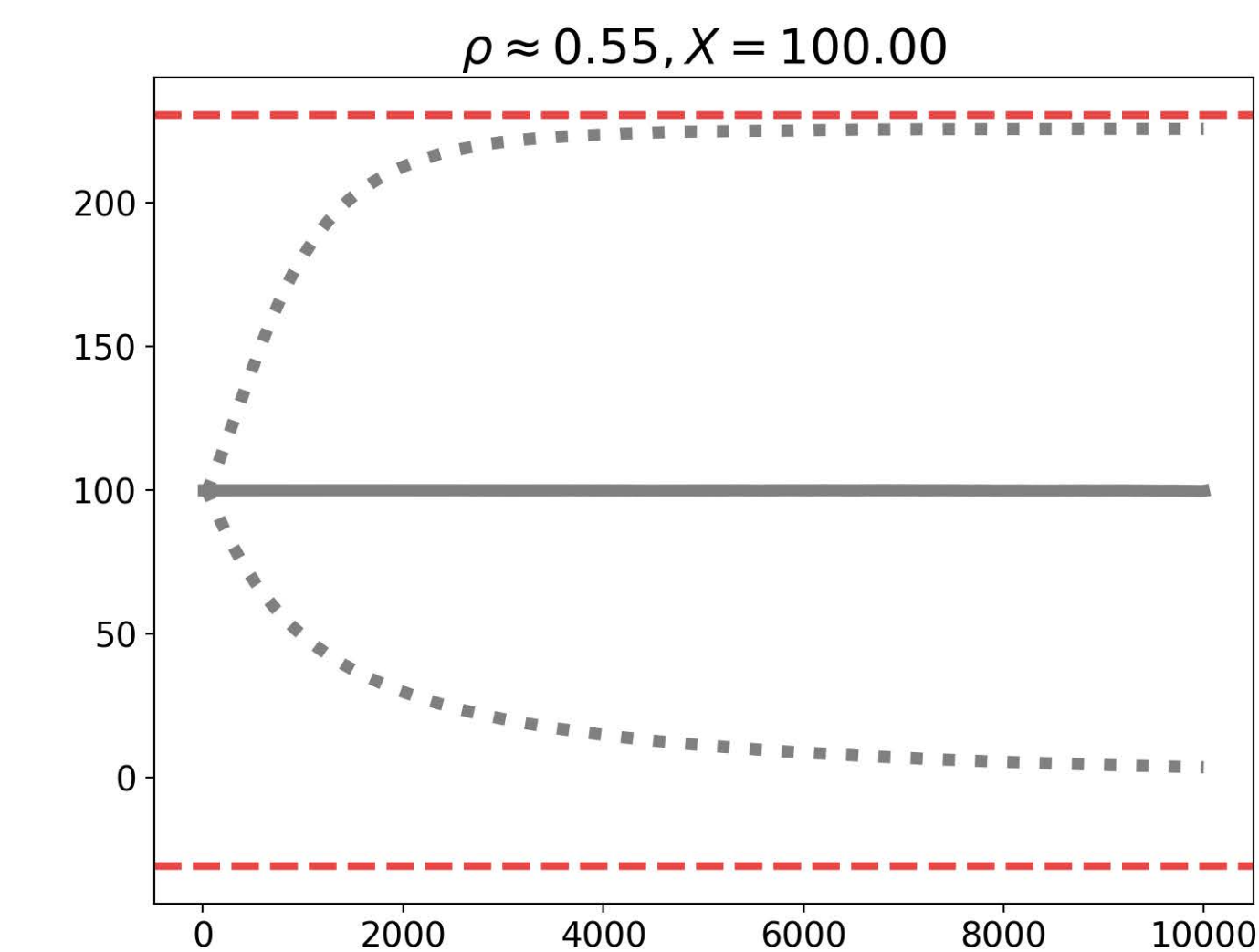
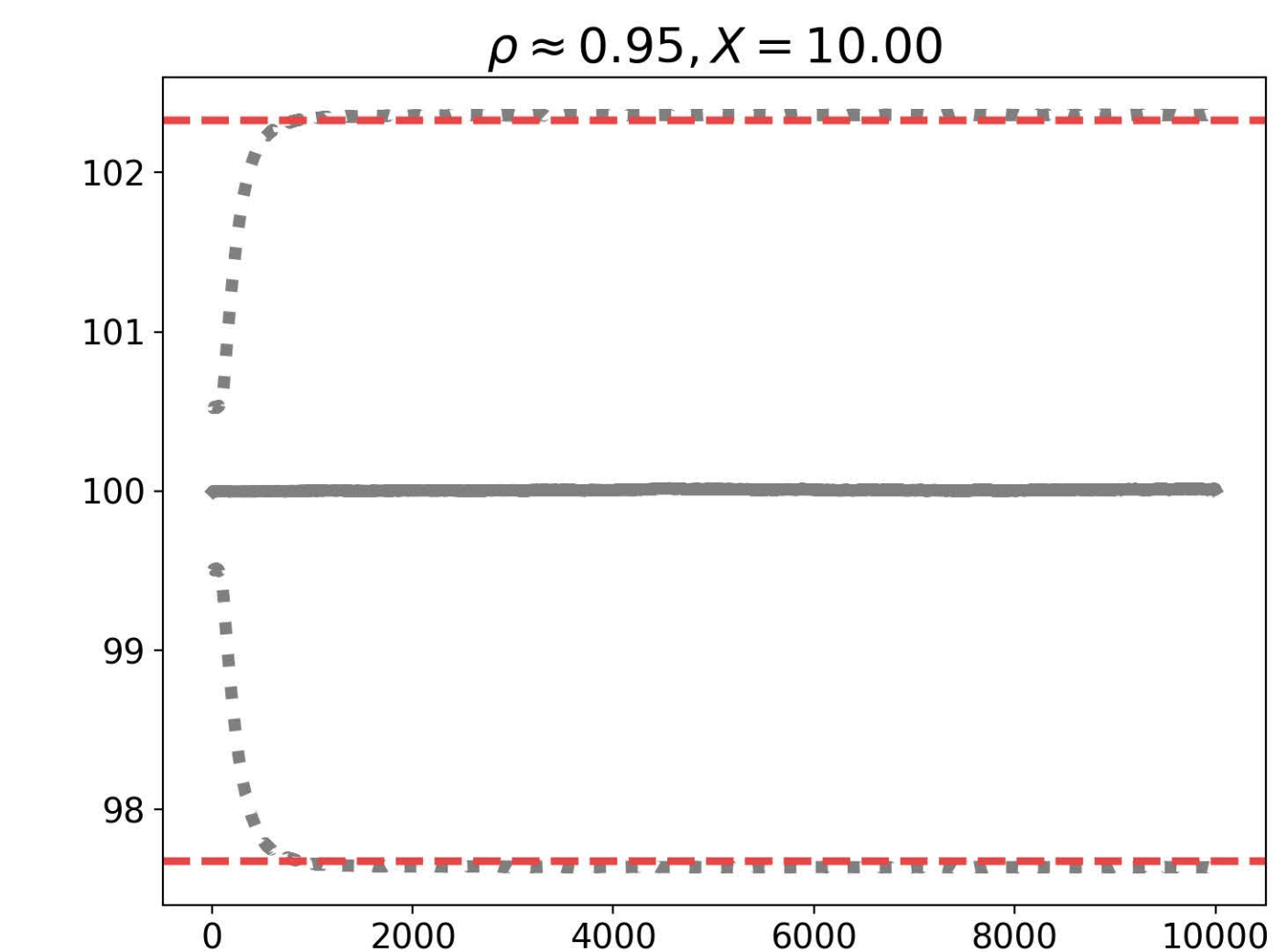
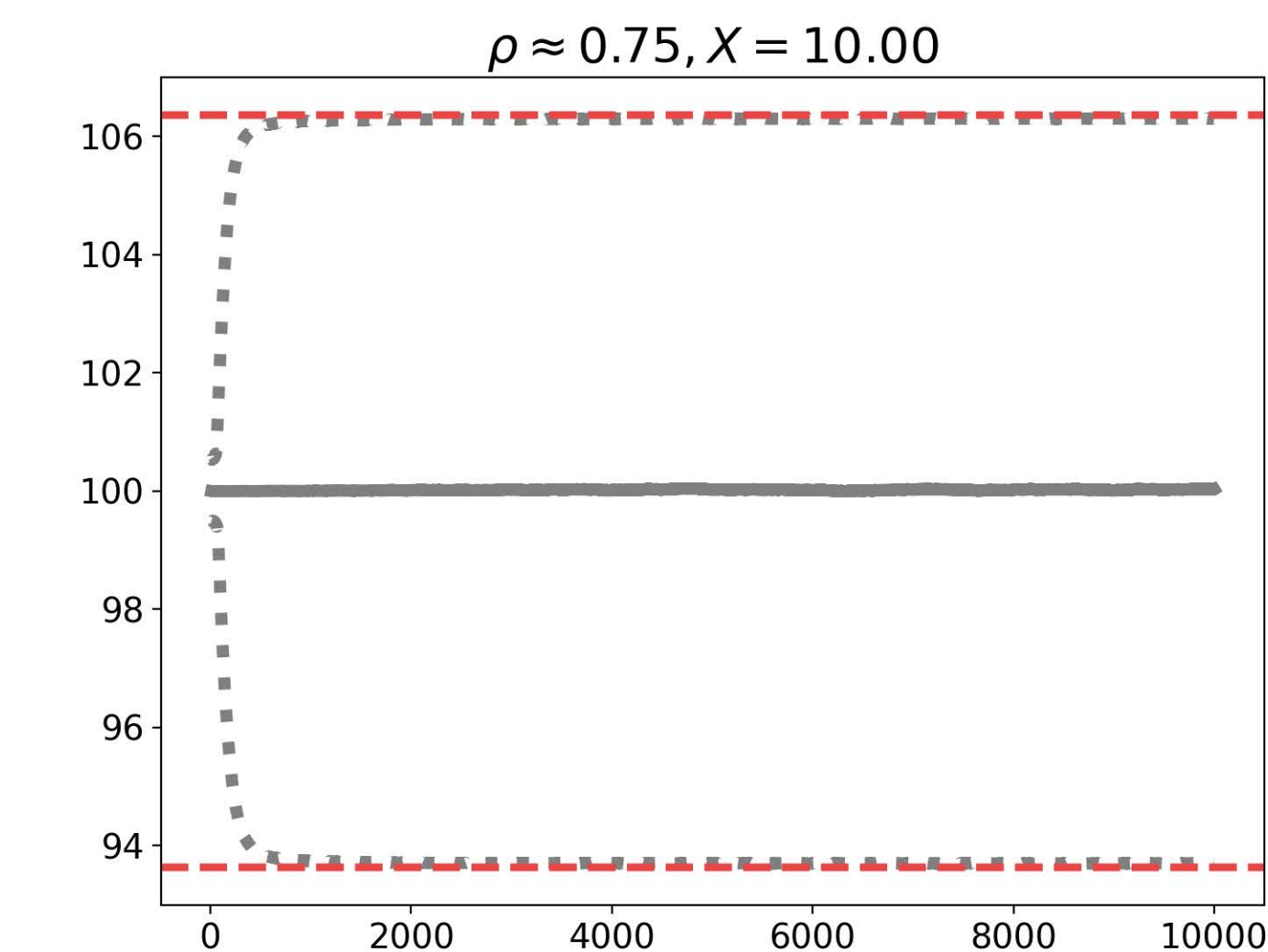
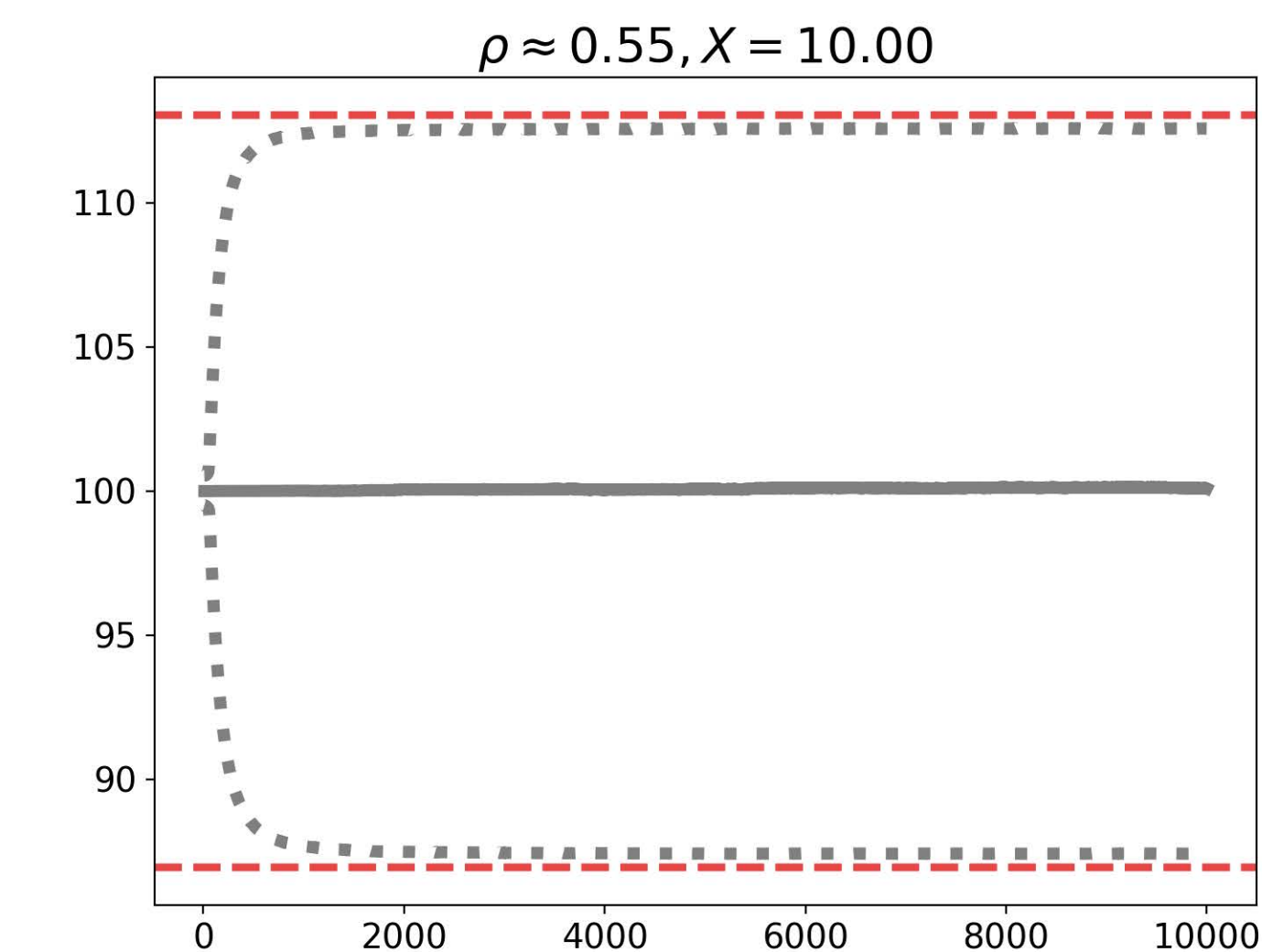
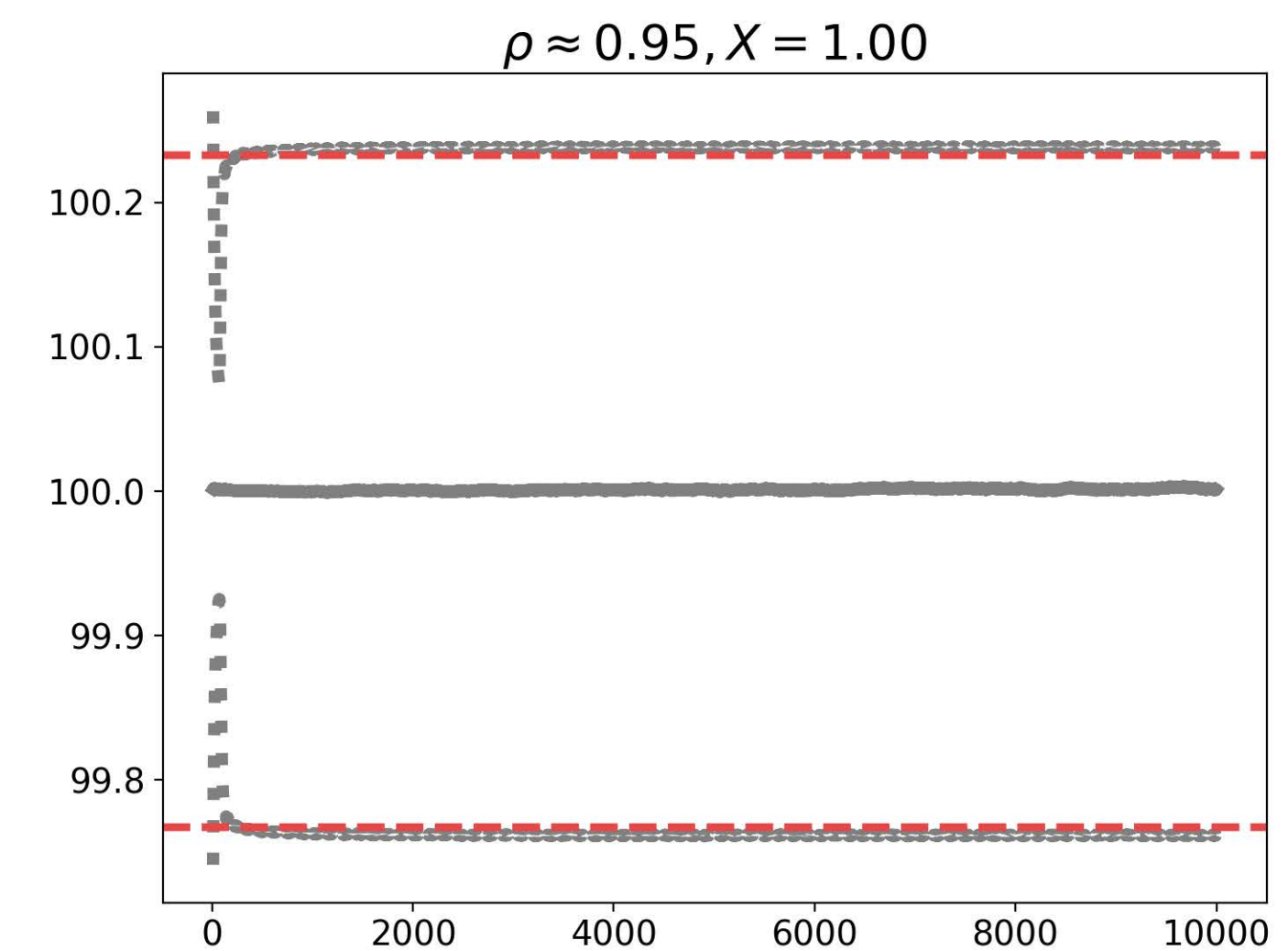
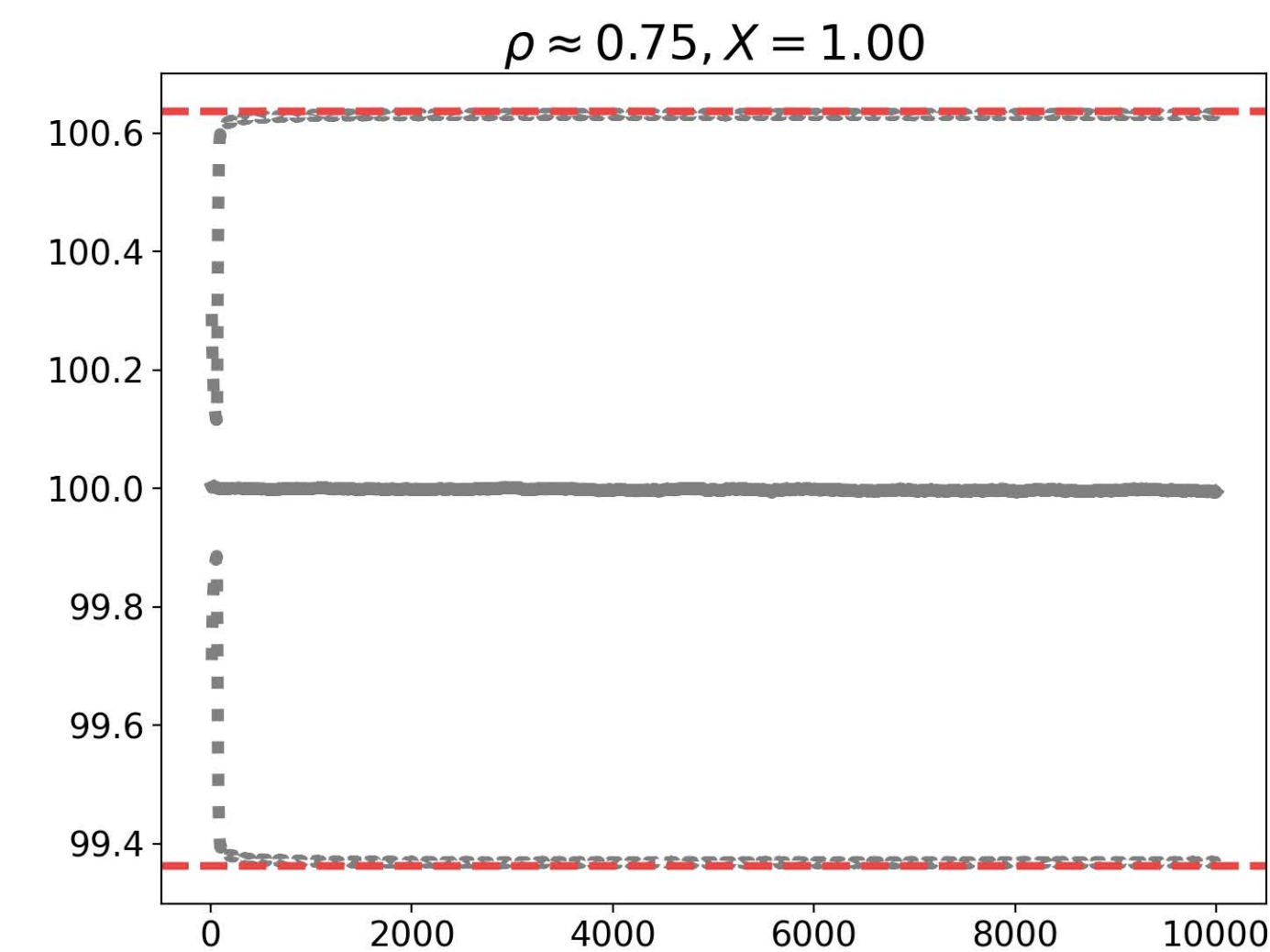
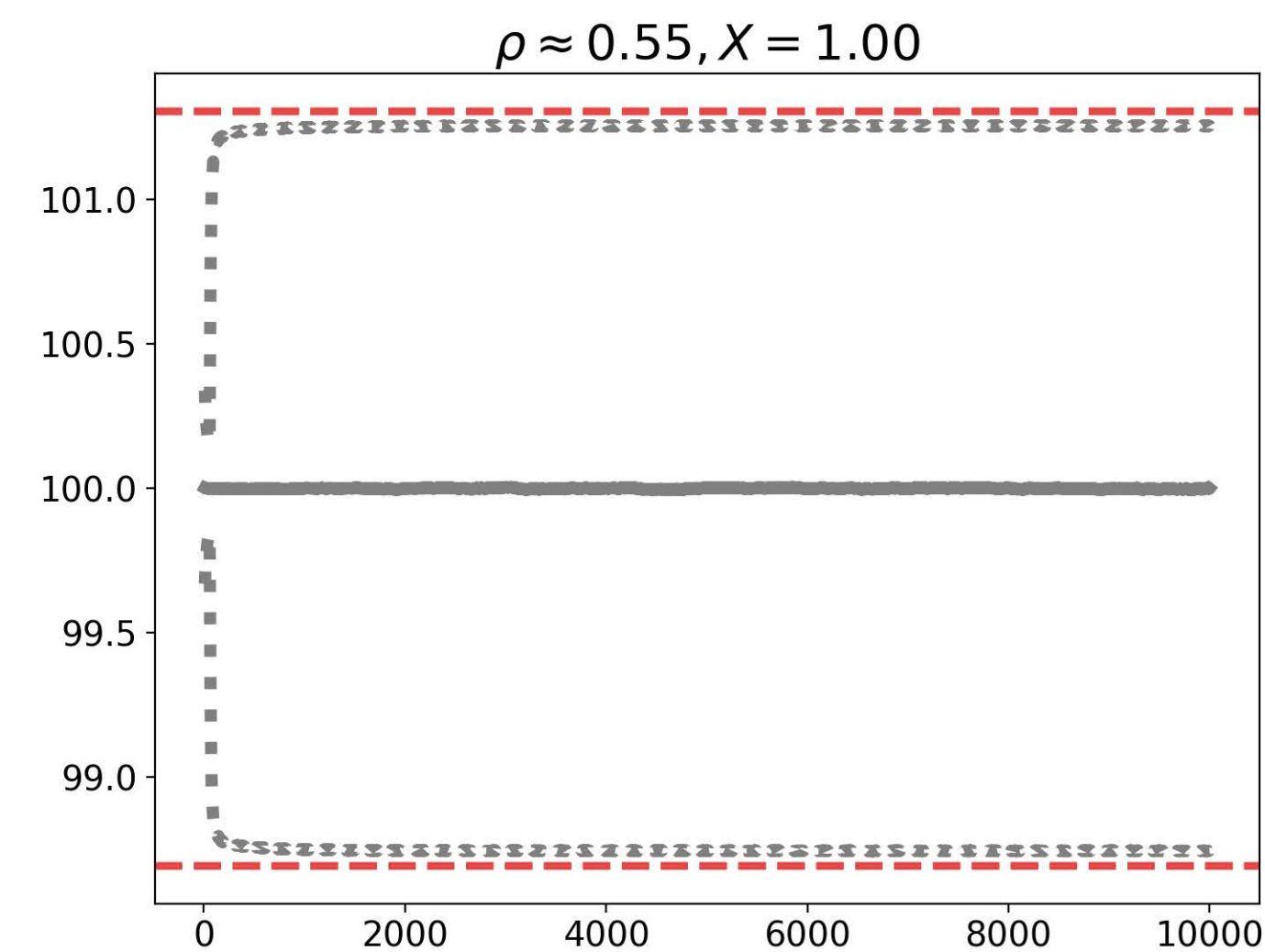
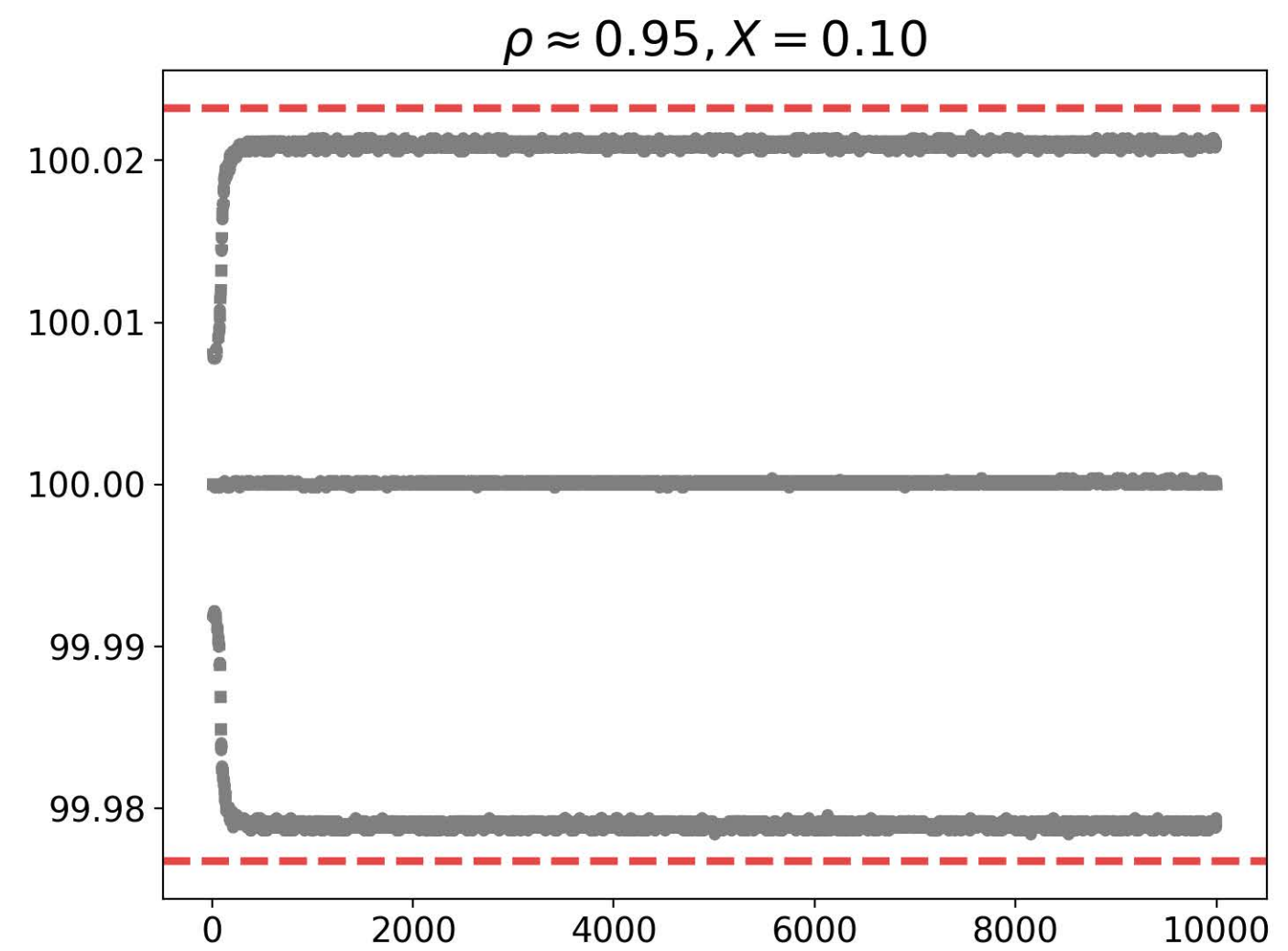
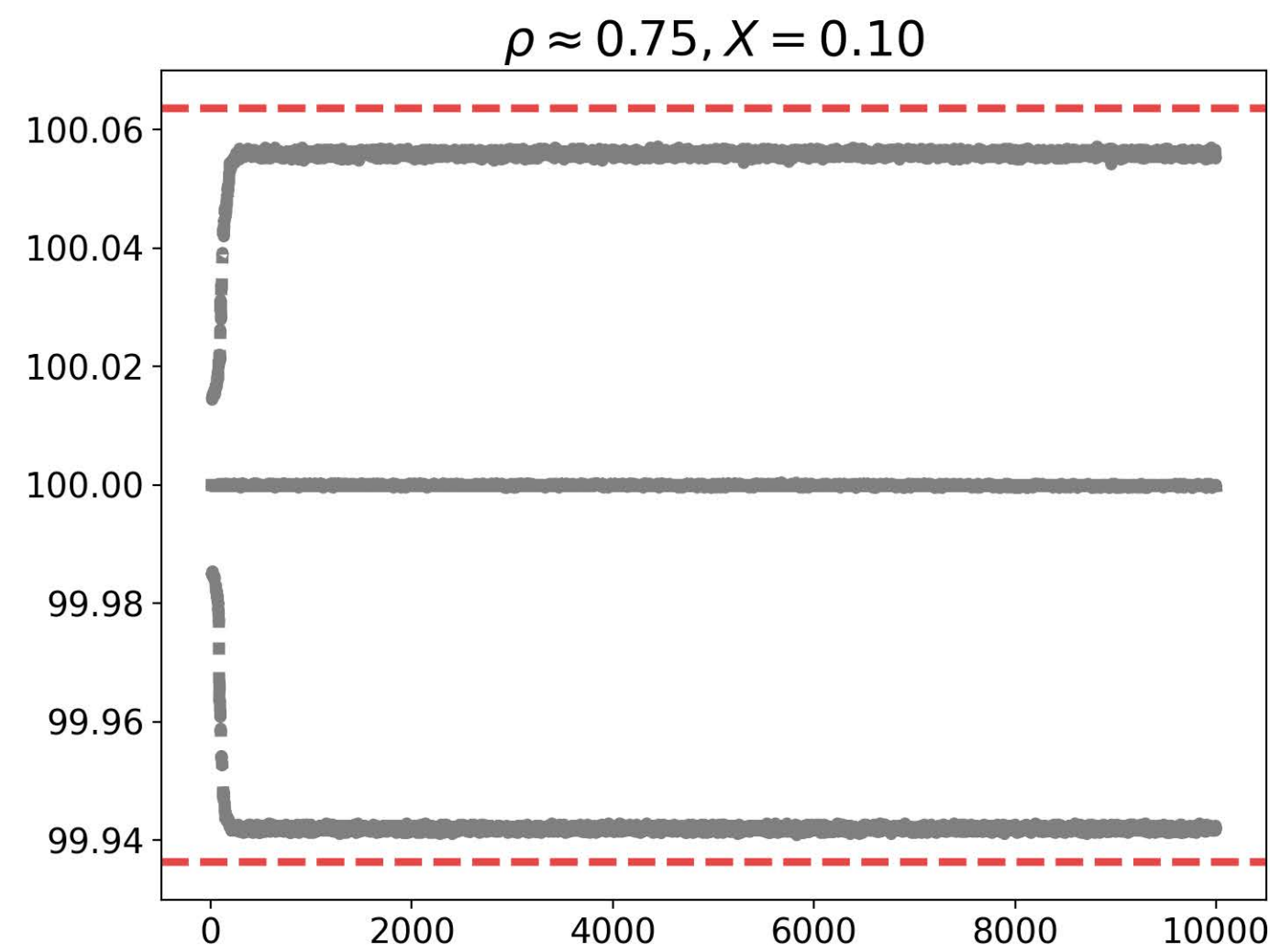
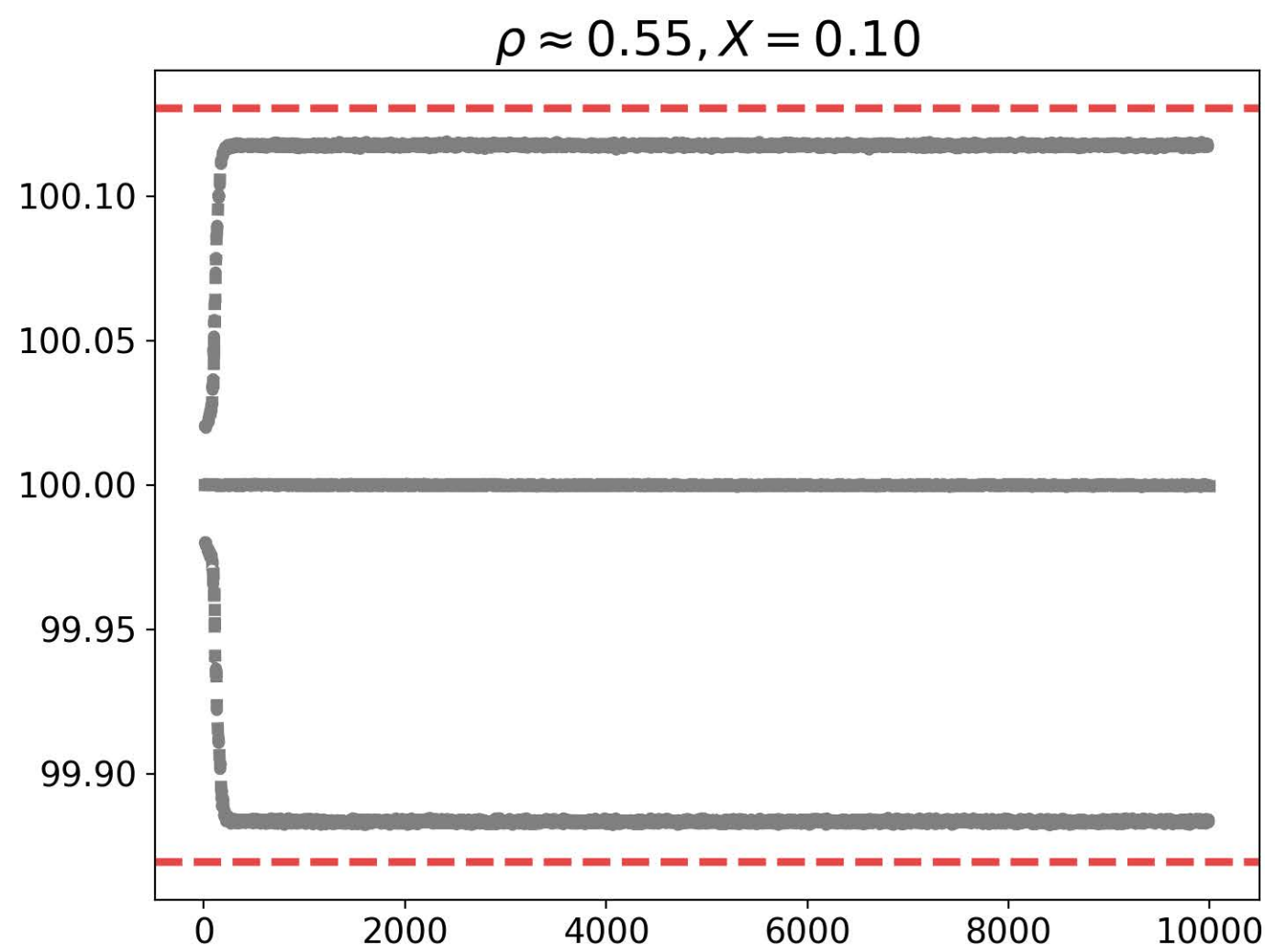


X = 100.0



Price $[p(t)]$

Time step $[t]$



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