

# AI Trading, Herd Behaviour, and Market Crashes: A Simple Simulation Story for Beginners

## 1 Introduction

This document explains, in plain language, a small computer simulation of an imaginary stock market. The goal is to understand how *automated* or *AI-like* trading strategies can sometimes make a market crash worse, and how in other situations the same kind of algorithms do not cause disaster because their actions partly cancel each other out.

We work with 20 pretend stocks and 30 “portfolios” (collections of stocks). We simulate prices over time and compare three scenarios:

1. A baseline world with a bad news event (a shock) but no AI trading.
2. A worst-case world where all AI traders panic and sell together.
3. A mixed world where AI traders behave differently, so some buy, some sell, and some do nothing.

All details are intentionally simplified: the numbers are made up and the model is not meant to predict real markets. It is just a story, backed by pictures, to build intuition.

## 2 Stocks, Portfolios, and the Market Index

### 2.1 Our toy market

We imagine a small stock market with the following ingredients:

- **20 stocks**, labelled S0, S1, …, S19. You can think of each as a different company.
- **30 portfolios**. A portfolio is simply a collection of stocks with certain percentages (weights) invested in each.

For example, one portfolio might look like this:

Stock	S1	S5	S9	S14
Weight	30%	10%	40%	20%

This means that if the portfolio has \$1,000 in total, it holds \$300 of S1, \$100 of S5, \$400 of S9, and \$200 of S14.

In the simulation, each of the 30 portfolios chooses between 5 and 10 stocks out of the 20, and assigns random weights that add up to 100%. This creates a lot of *overlap*: many portfolios share some of the same stocks.

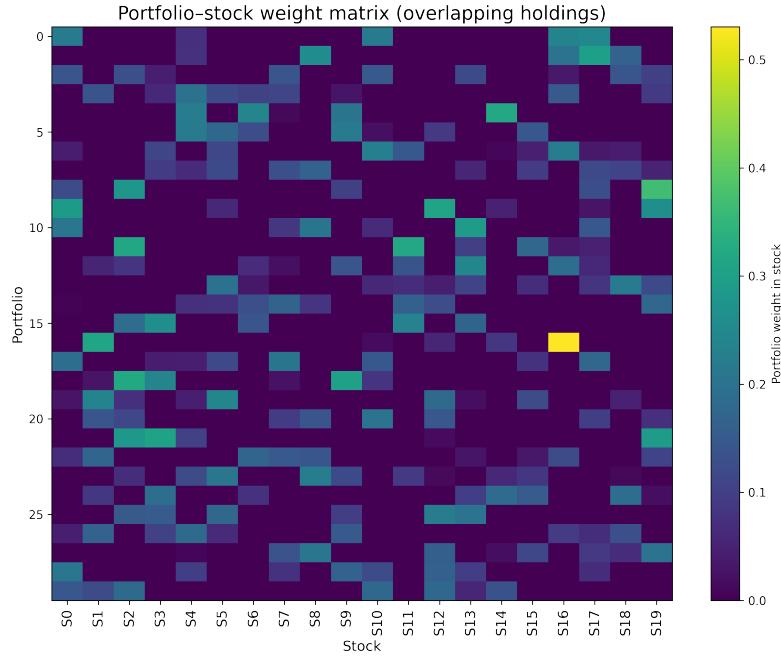


Figure 1: Portfolio–stock weight matrix. Each row is a portfolio, each column is a stock. Brighter colours mean a higher percentage of that stock in that portfolio. The pattern of coloured squares shows how holdings overlap between portfolios.

## 2.2 Visualising the overlap

Figure 1 shows this portfolio–stock structure as a heatmap.

You do not need to read exact numbers from this picture. The key message is simply: **many portfolios hold some of the same names**. That is what allows their trading decisions to interact and push prices around.

## 2.3 The market index

To keep track of the overall level of the market, we define a very simple *market index*:

**Index at time  $t$**  = average of all 20 stock prices at time  $t$ .

In real life, indices like the S&P 500 or NIFTY 50 use more sophisticated formulas, but the idea is similar: the index is a single number that summarises “how high the market is” on a given day.

In our graphs later, when we see the index line fall sharply, we will talk about a *crash*.

# 3 How Prices Move in the Simulation

## 3.1 Time steps and randomness

We simulate prices over 100 time steps. You can think of each time step as one day.

At each step, every stock has a small random price movement:

- On a typical day, the price might go up a little or down a little.
- Over many days, this creates a wiggly line, similar to what we see in real stock charts.

Mathematically, the idea is:

$$\text{return}_{t,s} = \text{base movement}_{t,s} + (\text{extra movement due to trading flows}),$$

where  $\text{return}_{t,s}$  is the percentage change of stock  $s$  on day  $t$ .

### 3.2 Trading flows and price impact

The second term in the formula, the *extra movement due to trading flows*, is where AI trading behaviour comes in.

We define:

- **Net flow** for a stock on a given day = (total buy pressure) minus (total sell pressure) coming from all portfolios.
- **Impact factor  $\alpha$** : a small number that says how strongly net flows push the price.

Then, very roughly,

$$\text{return}_{t,s} = \text{base movement}_{t,s} + \alpha \times \text{net flow}_{t,s}.$$

- If many portfolios try to *buy* the same stock, net flow is positive and the price gets an extra upward push.
- If many portfolios try to *sell* the same stock, net flow is negative and the price is pushed down further.

This is a simplified version of the idea that “prices move when orders hit the market”.

## 4 The Crash Day

### 4.1 Defining a crash day

To study how AI trading might change a crash, we first create a *bad news event* in the simulation.

- We choose a particular day, say day 40. This is our **crash day**.
- On that day, we add an extra negative shock to all stocks. For example, every stock gets an additional  $-8\%$  hit.

If there were no AI trading at all, this shock would already make the index drop. Later we will compare:

- How big the drop is with *no* AI selling.
- How big the drop becomes when *all* AI traders sell together.
- How big the drop is when AI traders behave differently from one another (some buy, some sell, some stay quiet).

## 5 Scenario A: Worst-Case Herding (All Bots Panic)

### 5.1 A simple AI rule

We give each portfolio a very simple, mechanical rule that stands in for an AI trading strategy:

**Sell rule:** “If there is a big negative shock, sell 20% of your position in each stock you hold.”

This captures a crude version of “cut your losses”: many risk-control and algorithmic strategies in real markets try to reduce exposure when prices drop sharply.

### 5.2 All bots react the same way

In the **worst-case scenario**, we assume that:

- Every portfolio uses exactly the same rule.
- They all interpret the shock on day 40 in the same way.
- They all trigger at the same time and try to sell at once.

Because portfolios overlap in their holdings, this means that many of them try to sell the same stocks on the same day. Net flows are very negative, and the impact term  $\alpha \times \text{net flow}$  pushes prices down further.

### 5.3 Comparing baseline vs worst-case

Figure 2 shows the market index over time in two cases:

1. **Baseline:** the shock happens, but there is no special bot selling (only random noise).
2. **Worst-case bots:** the same shock happens, and on that day all portfolios sell 20% of every stock they hold.

### 5.4 Story for beginners

In words:

- Imagine the news says something very bad about the economy.
- Even without AI, prices fall because everyone is worried.
- Now imagine that many investment algorithms, all over the world, are trained to sell a chunk of their holdings whenever they see a large drop.
- They all trigger at once. Suddenly a wave of sell orders hits the market, especially in the popular stocks held by many portfolios.
- This adds extra downward pressure, making the crash *sharper and deeper* than it would have been from the news alone.

That is exactly what the orange line in Figure 2 shows: the index not only falls on the crash day, it stays far below the baseline path afterwards.

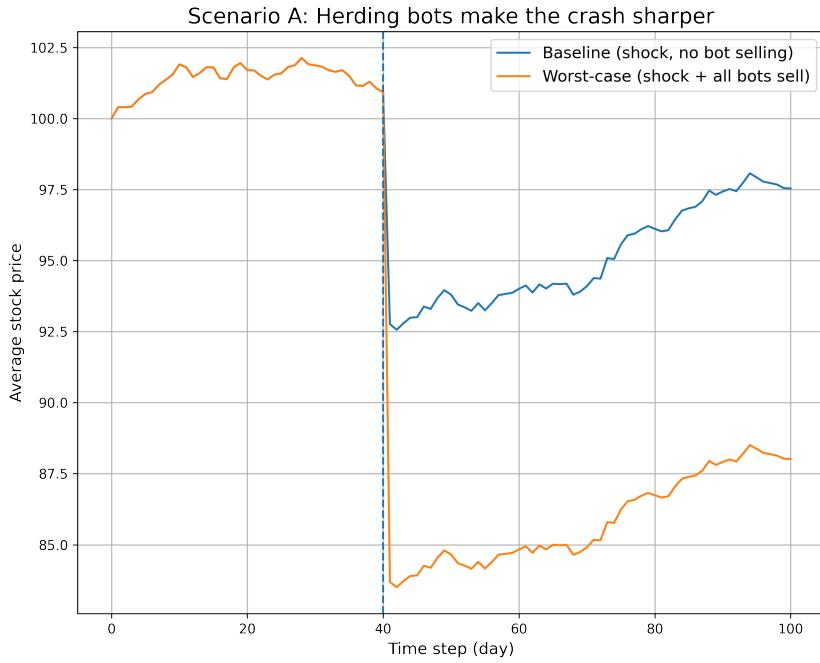


Figure 2: Scenario A: baseline (shock only) vs worst-case herding (shock plus all bots selling together). The dashed vertical line is the crash day. The orange line, with all bots selling, shows a much deeper and more persistent drop after the shock.

## 6 Scenario B: Mixed AI Behaviour (Balanced Out)

### 6.1 More realistic variety

The worst-case scenario assumes all bots are identical. In reality, however, trading rules differ:

- Some AI models might *buy* when prices fall, seeing a bargain.
- Others might *sell* to cut risk.
- Others might do nothing because their signals are not triggered.

In **Scenario B**, we model this by giving each portfolio, on each day, a random signal for each stock:

- $+1$  (buy a little),
- $0$  (do nothing),
- $-1$  (sell a little),

with certain probabilities. These signals are independent across portfolios, so actions partly cancel out.

### 6.2 Index paths in three scenarios

Figure 3 compares all three index paths:

- Baseline (shock, but no bots).
- Worst-case bots (shock plus all selling together).
- Mixed behaviour (shock plus diverse bots).

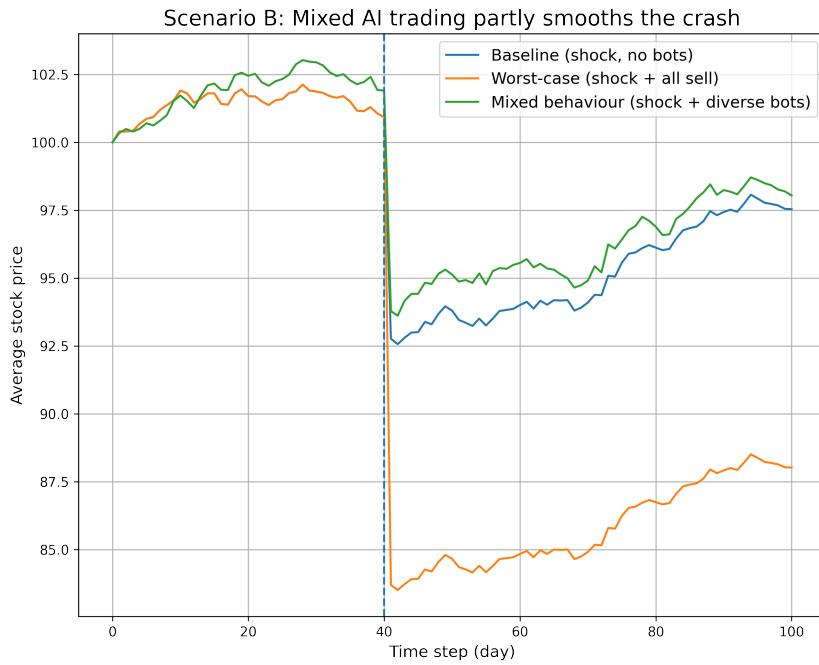


Figure 3: Scenario B: baseline (blue), worst-case herding (orange), and mixed AI behaviour (green). The crash day is marked by the dashed line. With diverse behaviour, the crash is still visible but much less extreme than in the worst-case.

### 6.3 Story for beginners

Reading Figure 3:

- The **orange line** (worst-case bots) still shows the deepest crash and the weakest recovery.
- The **blue line** (no bots) drops on the crash day but then gradually recovers as random movements add up.
- The **green line** (mixed behaviour) is somewhere in between, and often above the blue line after the crash.

This demonstrates an important point:

*AI trading is not automatically dangerous. It becomes risky when many systems are highly similar and all move in the same direction at the same time. When AI strategies are diverse, their actions can partly balance out and even stabilise the market.*

## 7 How Much Does the Market Fall on the Crash Day?

### 7.1 Measuring the “one-day crash”

To make the comparison even clearer, we compute the percentage change in the index from day 40 to day 41 in each scenario:

$$\text{1-day change} = \frac{\text{Index after crash day} - \text{Index before crash day}}{\text{Index before crash day}} \times 100\%.$$

We then plot these three numbers as a simple bar chart.

### 7.2 Bar chart of crash sizes

Figure 4 shows the result.

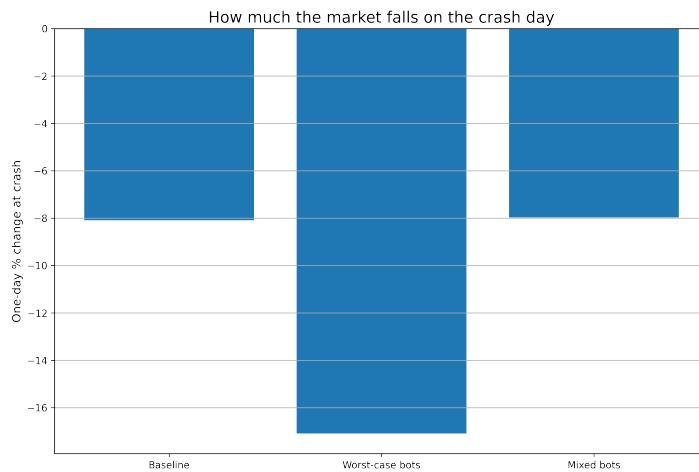


Figure 4: One-day percentage change of the market index on the crash day in the three scenarios. The worst-case herding scenario produces the largest downward move; the mixed AI behaviour reduces the size of the crash compared to the worst case.

Even without reading exact numbers, we can see the pattern:

- The **baseline** drop is moderate.
- The **worst-case bots** drop is much larger (the bar is far below the others).
- The **mixed behaviour** drop is between them, and closer to the baseline than to the worst case.

This visual reinforces the story told by the time series graphs.

## 8 Putting It All Together

### 8.1 Key concepts summarised

Let us summarise the main ideas in plain language.

**Stocks and portfolios.** We built an imaginary market with 20 stocks and 30 portfolios. Each portfolio holds a mix of stocks, and many portfolios overlap in what they own.

**Market index.** We used the average stock price as a simple index: one number that tracks overall market level.

**Crash day.** On one chosen day, we added a big negative shock to all stocks. This represents a piece of very bad news (for example, a crisis).

**AI trading rules.** We imagined simple mechanical “AI-like” rules: sell a fixed fraction when prices drop sharply, or apply small random buy/sell signals each day.

**Herd behaviour.** When all portfolios share the same rule and react at the same time, their orders stack up and they push prices much further down than the news alone would.

**Diversity of behaviour.** When different portfolios behave differently, some buying while others sell, the net effect is more moderate. Their trades partly cancel each other out, smoothing the market response.

## 8.2 What does this say about real markets?

Real financial markets are vastly more complex than our little model: they have thousands of stocks, millions of investors, many kinds of AI, and strict regulations and safeguards. However, the core lessons are still useful:

1. **AI can amplify shocks.** If many algorithms use similar strategies and are allowed to trade aggressively, they can turn a bad news event into a much deeper crash by all selling at once.
2. **Diversity stabilises.** Differences in models, objectives, and time horizons can make markets more resilient, because participants are not all doing the same thing at the same time.
3. **Risk comes from similarity and scale.** The danger is not AI itself, but the combination of:
  - very similar models,
  - very fast reactions, and
  - very large money flows.

When those three line up, herding behaviour becomes powerful.

## 8.3 Final remark

The simulation and figures in this document are not forecasts. They are a story-telling tool: a way to see how automatic trading rules might interact with each other and with a shock. They highlight a simple but important idea:

*In markets, it is not just what each trader does individually that matters, but how many of them try to do the same thing at the same time.*

Understanding that idea is a first step towards thinking carefully about how we design and regulate AI trading systems in the real world.