A Pedagogical framework for **teaching Econophysics** through contrasting Self-Organized Criticality in the Bak-Chen-Scheinkman-Woodford Model with Real Business Cycle Theory Through Rationality Debates

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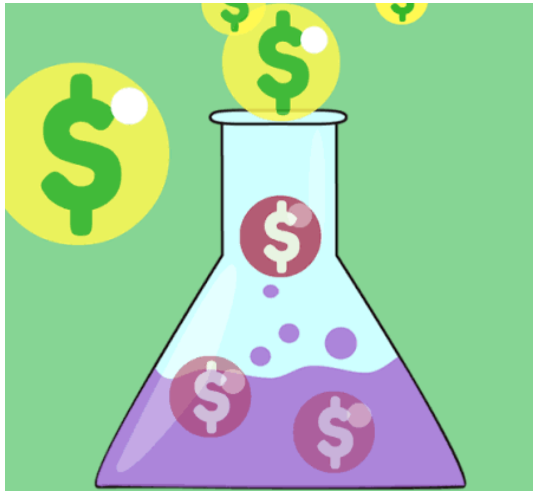
Why physicists should teach and learn econophysics.

The quantitative skills of a physics postgraduate are **exactly what finance now hires for**. If we don't teach our students to model the economy, we leave it to be modelled by **everyone** but us.

5 000 / yr

SA's PhD target by 2030 (up from ~3 300 in 2018) — a deliberate expansion



~2/3

of employed academics are in non-permanent jobs — the push out of academia

~18%

of SA PhD holders work in jobs unrelated to their field

Sources: DSI–NRF / SciSTIP National PhD Tracer Study (2000–2018); CHE VitalStats; NRF commentary.

Physics models already used to describe the economy

Physics model	Economics counterpart	Since
Brownian motion / diffusion	Bachelier’s speculation theory & the Efficient Market Hypothesis	1900 / 1965
Ising model (interacting spins)	Herding & opinion-dynamics markets (Bornholdt, Kirman)	1990s
Self-organized criticality (sandpile)	Business cycles & systemic cascades (Bak–Chen–Scheinkman–Woodford)	1993
Heat / diffusion equation	Black–Scholes option pricing (a mathematical identity)	1973
Statistical-mechanics entropy maximization	Utility maximization & discrete-choice (logit) economics	1970s–

The recipe

1 Recap the physics	State the physics model cleanly: its rules, its behaviour.
2 Map the analogy	Line it up against an economics model , what corresponds to what?
3 Scrutinise the physics	Apply the physicist’s tools (distributions, scaling, correlations) to the physics model.
4 Apply the SAME lens	Run the identical analysis on the economics side and see what it implies.
5 Be honest	Where the model fails, say so. The failure is the most instructive part. **(Visualisations)**

Deep Dive 1 — Brownian motion vs the Efficient Market Hypothesis

When the physics model **fails** honestly

Recap the physics, then map the analogy

Physics: Brownian Motion

- a particle takes independent random steps
- increments are Gaussian, memoryless
- spreads as √t (the diffusion law)
- signature: normal distribution, zero autocorrelation
- $dx = \mu\, dt + \sigma\, dW_t$

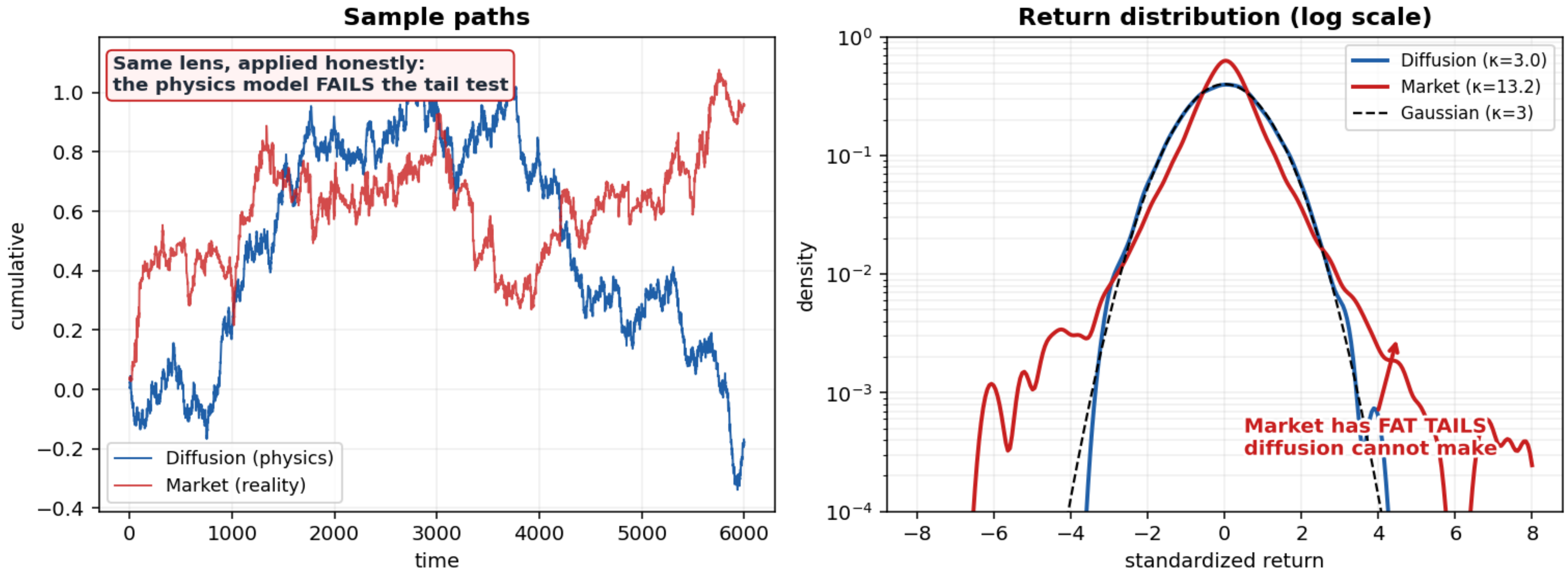
Economics: Efficient Market Hypothesis

- prices absorb information instantly
- so price changes are unpredictable
- returns ≈ independent random draws
- prediction: returns should look Gaussian & uncorrelated

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \mu + \sigma\varepsilon_t$$

Brownian motion	EMH	meaning
position $x(t)$	**log-price** $p(t) = \ln P(t)$	the state
drift μ	**expected return / risk-free rate**	deterministic trend
diffusion σ	**volatility**	size of random shocks
Wiener increment dW_t	**information shock** ε_t	the randomness
independent increments	**weak-form efficiency**	no memory / no arbitrage
$\mathrm{Var} \propto t$	**volatility** $\propto \sqrt{t}$	the diffusion law

Be honest: the physics model fails



Note: pure randomness reproduces the *absence of predictability* but not the fat tails of real markets.

Shonkwiler, R.W. (2013). *Geometric Brownian Motion and the Efficient Market Hypothesis*. In *Finance with Monte Carlo*, Springer. doi:10.1007/978-1-4614-8511-7_1

Deep Dive 2 — Ising Model vs a Herding Market

When the physics model **succeeds**

Recap the physics, then map the analogy

Physics: Ising model

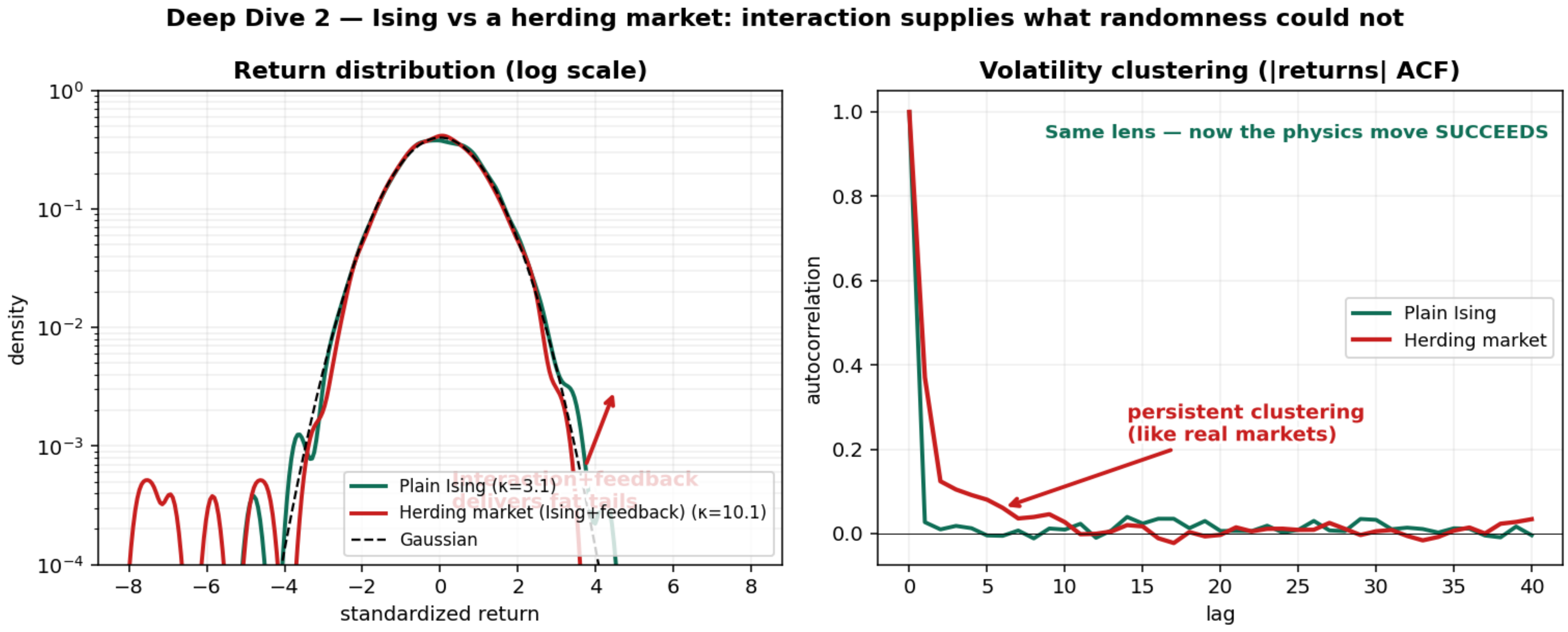
- spins $s_i = \pm 1$ on a lattice
- neighbours prefer to align (coupling J)
- a critical temperature separates order from disorder
- near criticality: large, correlated fluctuations
- $$H = -J \sum_{\langle i,j \rangle} s_i s_j - h \sum_i s_i$$

Economics: herding market

- trader = spin: buy (+1) or sell (−1)
- agents copy their neighbours (social coupling)
- sentiment can tip collectively
- question: do markets sit near a critical point?
- $$h_i(t) = J \sum_{\langle i,j \rangle} s_j(t) - \alpha\, s_i(t)\, |M(t)|$$

Ising	Herding market	meaning
spin $s_i = \pm 1$	trader action: buy / sell	the microscopic state
coupling J	imitation strength	how strongly agents copy neighbours
external field h	external news / sentiment bias	global push on all agents
temperature T ($\beta = 1/k_B T$)	idiosyncratic noise / "rationality"	deviation from the crowd
magnetization M	net market sentiment	aggregate order parameter
critical point T_c	market on the edge of a herd	fluctuations diverge → crashes
— (absent in plain Ising)	contrarian term $-\alpha\|M\|$	the ingredient that matches markets

Be honest — and note the refinement that makes it work



Note: Plain Ising still looks Gaussian — but adding the ***herding feedback*** (traders react to the crowd) yields fat tails AND volatility clustering.

Bornholdt, S. (2001). *Expectation bubbles in a spin model of markets*. Int. J. Mod. Phys. C, 12(5), 667–674. doi:10.1142/S0129183101001845

Deep Dive 3 — Self-Organized Criticality (BCSW) vs Real Business Cycle theory

Working the recipe honestly — when it ends in a **draw**

Two rival explanations of the business cycle

BCSW (physics / SOC)

- Each site I on the on a lattice holds z_i grains. Drive by adding grains, when a site reaches z_c it topples:

  If $z_i \geq z_c$: $\quad z_i \to z_i - z_c, \qquad z_j \to z_j + 1$

  for each neighbour j

  where avalanche sizes s follow a power law:

  $P(s) \sim s^{-\tau}$

Sandpile (SOC)	BCSW	meaning
site i	firm / sector i	the unit
grains z_i	inventory / order backlog	local state variable
threshold z_c	production / capacity threshold	when the unit "fires"
toppling $\to$ neighbours	placing orders on suppliers	how activity propagates
lattice neighbours	supply-network links	interaction topology
adding a grain (drive)	a small demand shock	the small independent input
avalanche size s	size of an output fluctuation	the collective event
power law $P(s) \sim s^{-\tau}$	scale-free business-cycle sizes	the SOC signature
self-organizes to criticality	economy sits near criticality	the central claim

RBC (economics)

- Firms on a production network; firm i holds inventory / faces demand near a threshold. A firm produces (a "topple") when downstream orders push it over a critical level, sending orders to its suppliers (neighbours) — exactly the toppling rule, reinterpreted:

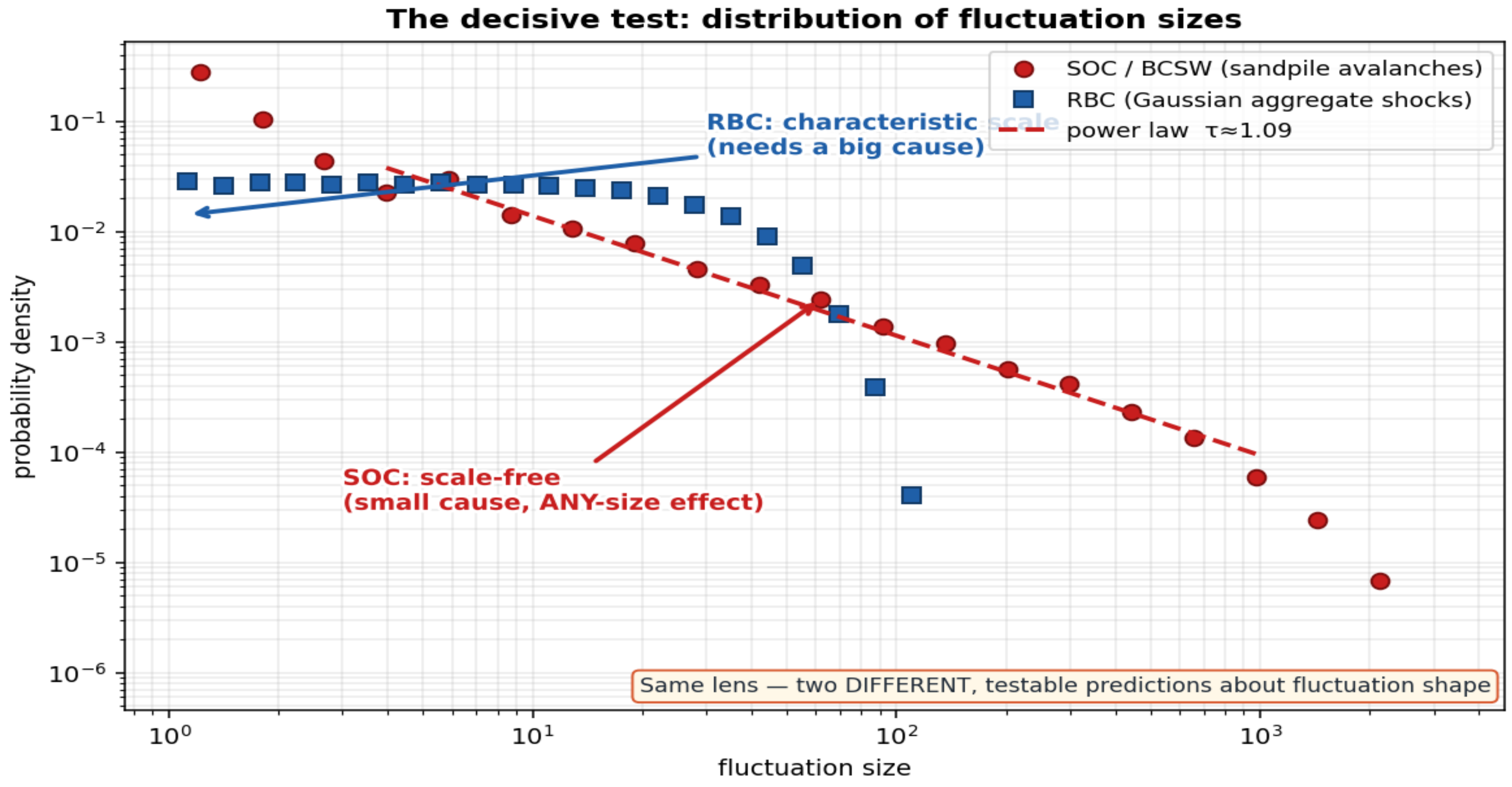
  if $\mathrm{demand}_i \geq \mathrm{threshold}_i$:

  firm produces→places orders on upstream suppliers

  Small, independent sectoral demand shocks propagate upstream as **production avalanches**, giving aggregate output fluctuations with a power-law size distribution:

  P(fluctuation size) $\sim s^{-\tau}$

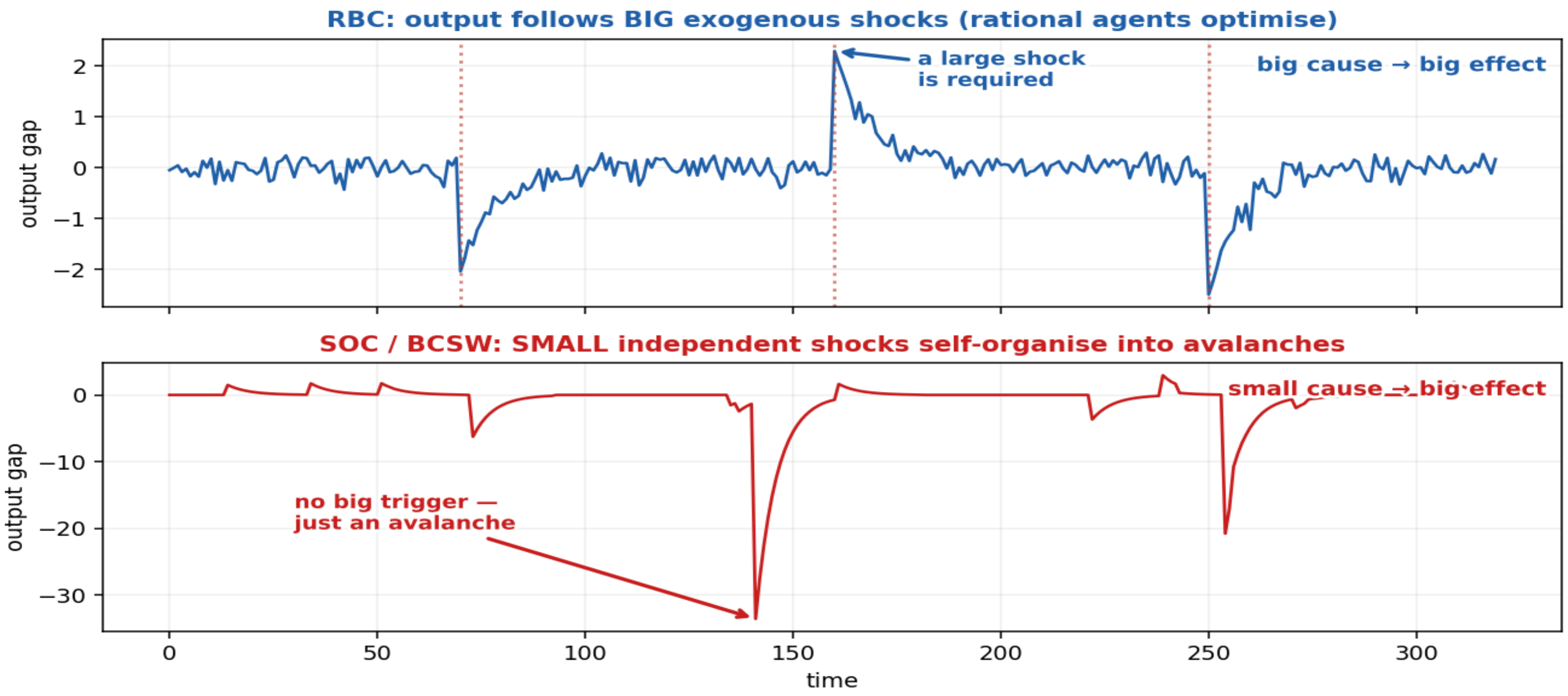
Same lens, two different testable predictions



The straight red line means SOC has no characteristic fluctuation size (any size is possible), while the curved blue points mean RBC does so one plot, two testably different predictions.

SOC/BCSW: Bak, Chen, Scheinkman & Woodford, *Ricerche Economiche* 47(1):3–30 (1993). doi:10.1016/0035-5054(93)90023-V

Must a big effect have a big cause?



Note: The top and bottom produce the same-sized cycles from opposite causes — RBC needs a big shock, SOC doesn't — which is the whole debate in one picture: must a big effect have a big cause?

Bak, Chen, Scheinkman & Woodford, *Ricerche Economiche* 47(1):3–30 (1993). doi:10.1016/0035-5054(93)90023-V

Summary and Closing remarks

- Success implies models are approximately analogous, and further physics tools and be inferred to explore more results.
- Failure implies an honest gap between models, and opportunity for more research.
- Draw implies an opportunity for more research

Thank you