Financial market simulation on a scale-free TPI network

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Scale-free **T**rade **P**osition **I**nfluence (**TPI**) Network Model

- **Information**: propagated over large distances throughout a network of market participants who make trading decisions under **mutual influence**.
- **Barabási-Albert Scale-free network**: network created with preferential attachment. Few high degree nodes (Hedge Funds) and many low degree ones (smaller traders).
- **TPI interaction**: large nodes with many connections represent influential and institutionalized traders. Smaller traders will determine and update their market positions (buy/sell) influenced by positions of the neighbours.
- **System dynamics**: relationship in financial markets are non-linear and small local changes can lead to large, global effects.
- **Feedback loop**: avalanches emerge as changes in market price affect trading behavior, which in turn affects the market price again.

Network definition

Biondo et al. (2015) proposed a **Small World** network. However, it presents some major shortcomings:

- Spatial nature of the relationships
- No meaningful leader in the network
- High concentration of informed traders

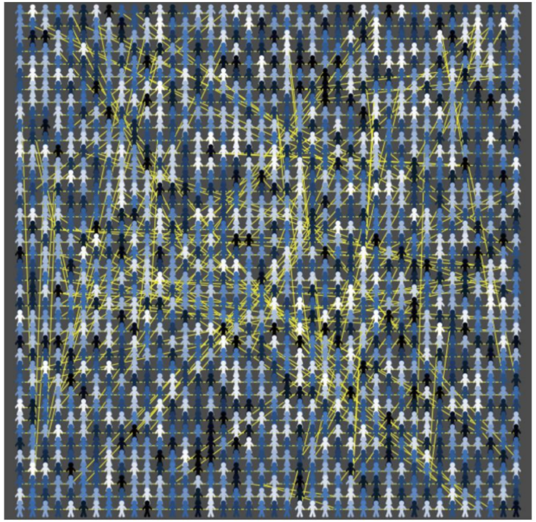


FIG. 1. (Color online) An example of the 2D small world lattice adopted in our model (with $n = 40$). Traders are distributed on a square network where short- and long-distance links are visible. Agents are coloured differently in order to represent their levels of information: the brighter a trader is, the more informed she is. Initial levels of information are distributed randomly. See text for further details.

Biondo et al. (2015)

Network composition

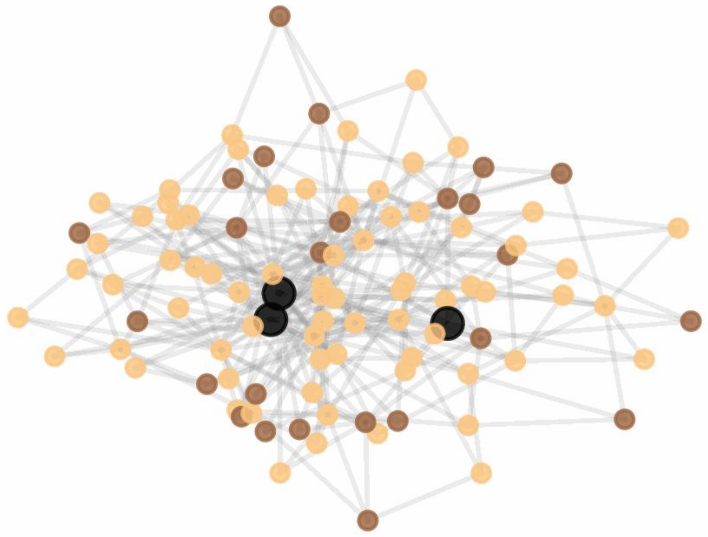
In our simulations we use a total of

N_{nodes}= 1000. They are comprised of:

Hedge funds
10% of total population. They follow a precise strategy dictated by a target profit for each trade.

Influenced traders
65% of the total population.

Random traders
25% of the total population.



Market price & Trading volumes

At each timestep the market price is determined by the following formula:

$$P = \eta * (V_B - V_S) * \chi$$

where V_B and V_S are the buy and sell volumes, respectively, η is a scaling factor, and χ is an exponentially distributed random variable with expected value

$$\lambda = \Delta = |V_B - V_S|$$

The size of each node's position (i.e. the trade size) is a uniformly distributed random variable

$$S \sim U(a, b)$$

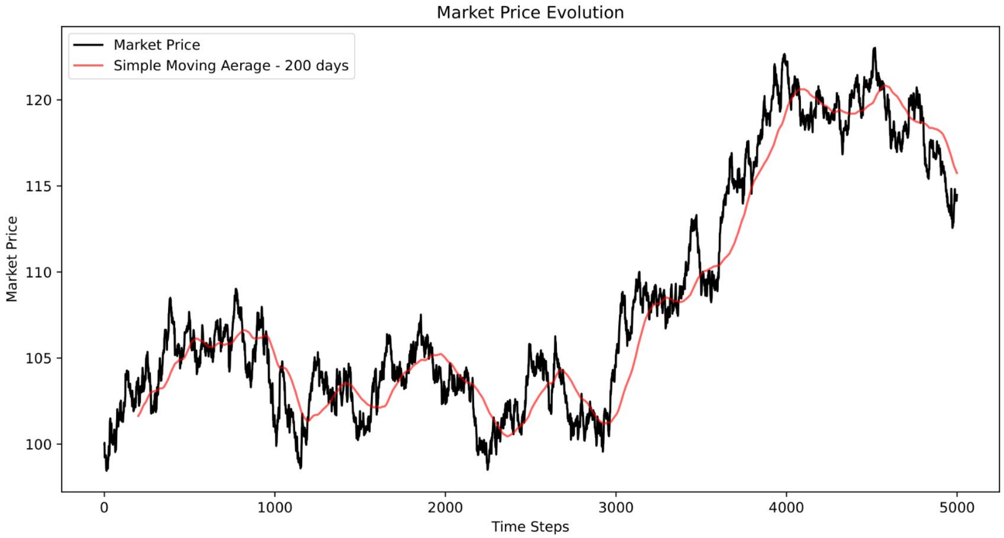
Where a,b represent respectively the minimum and the maximum trade size of the node's class.

Market price behavior

Sample size:
192 different initial conditions
1.920.000 simulated time steps

Research questions:

- How can we identify **avalanches** in the price?
- Which aspects of the market dynamics exhibit **self-organized criticality**?
- Is a simple TPI network sufficient to re-create a stylized-factual market?

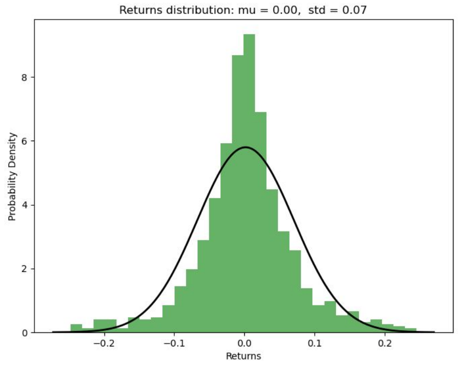


Stylized facts

Stylized facts are well-known facts found in any real world market.

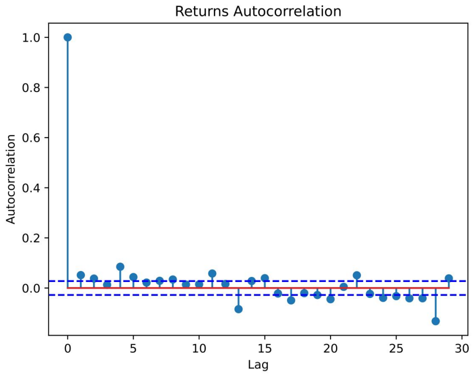
To assess these facts on our simulated market we measure:

- Returns distribution
- Squared returns (volatility clustering)
- Autocorrelation of returns and squared returns

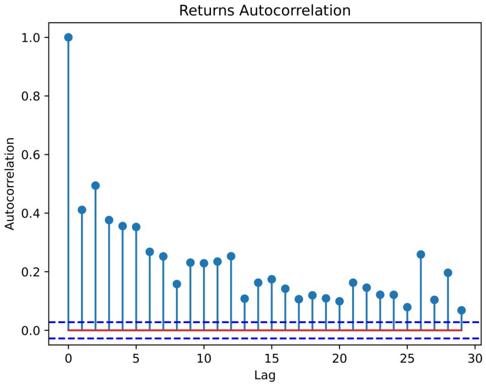


(a) Returns distribution

(b) Squared returns time series



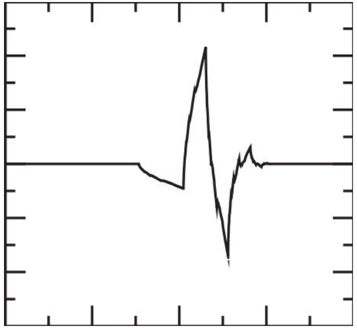
(c) Returns ACF



(d) Squared returns ACF

Detect avalanches in the market

We used wavelet analysis as inspired by Bartolozzi et al. (2005)



Why Wavelets?

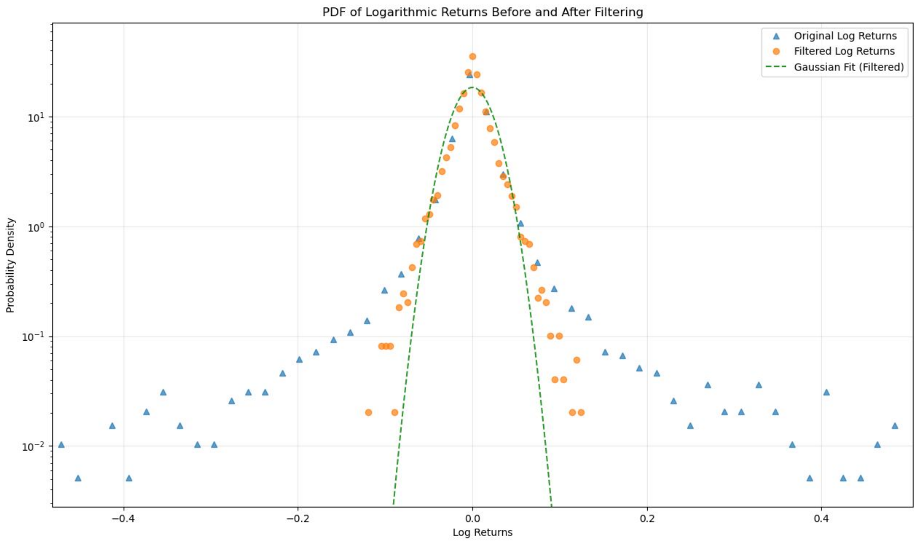
- Financial markets show irregular, **bursty activity**

Wavelet Basics

- Allow time-scale decomposition of data using a localized function called the "**mother wavelet**"
- Wavelet transform generates coefficients indicating how well the data matches the wavelet at different time steps and scales
- Large coefficients represent high-activity, small coefficients correspond to stable market behavior

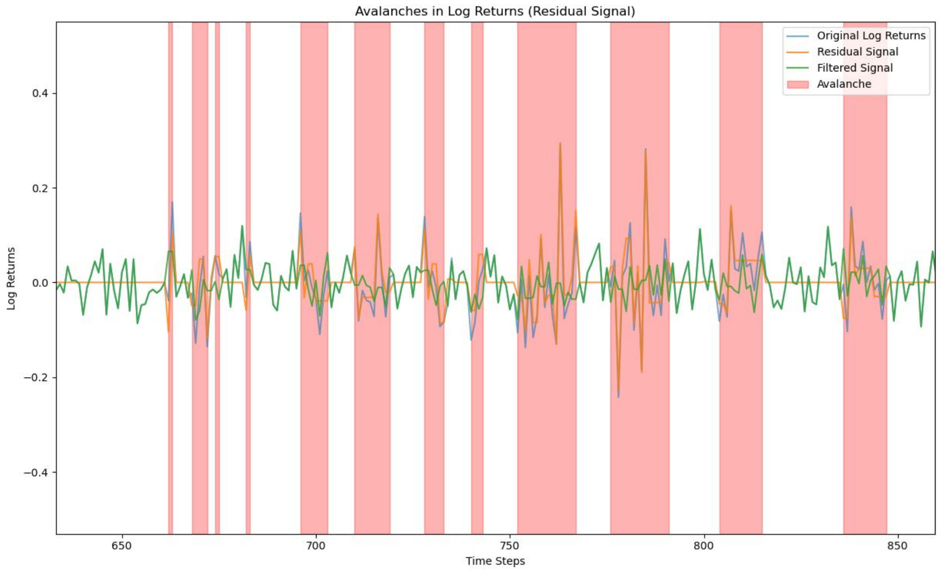
Filtering and reconstruct signal

- Coefficients below a threshold are set to zero, removing noise from the time series
- Inverse wavelet transform reconstructs a smoothed version of the original signal



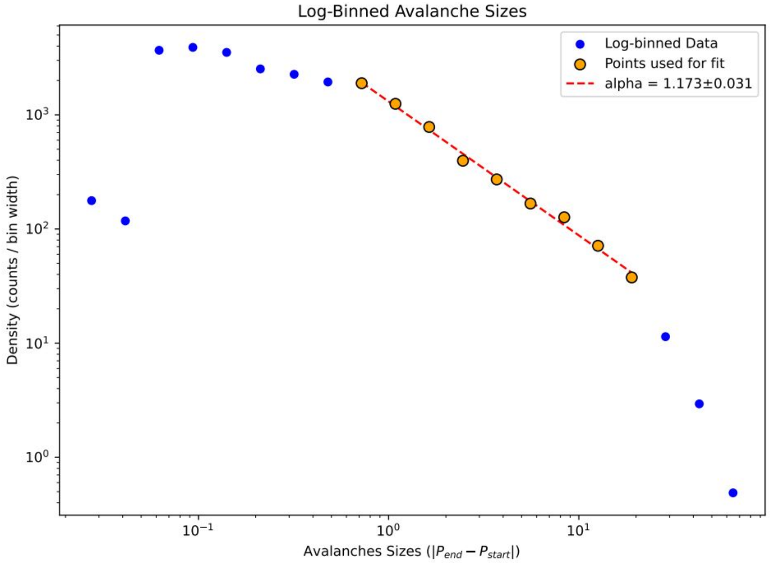
Detect avalanches in the data

- **Residual signal**: difference between the original and filtered data
- **Avalanches**: detected as regions in which the residuals are larger than a small cut-off
- Avalanches are characterized by size, duration and laminar times
- **~6000 avalanches identified**

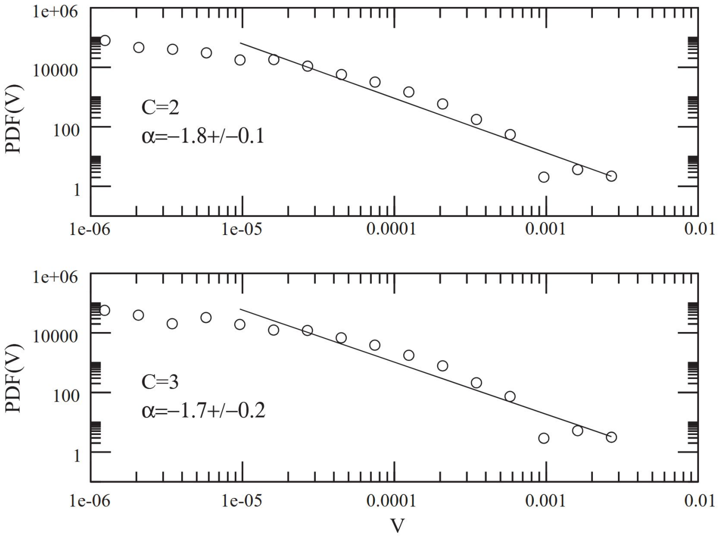


Avalanches sizes

Power-law distribution



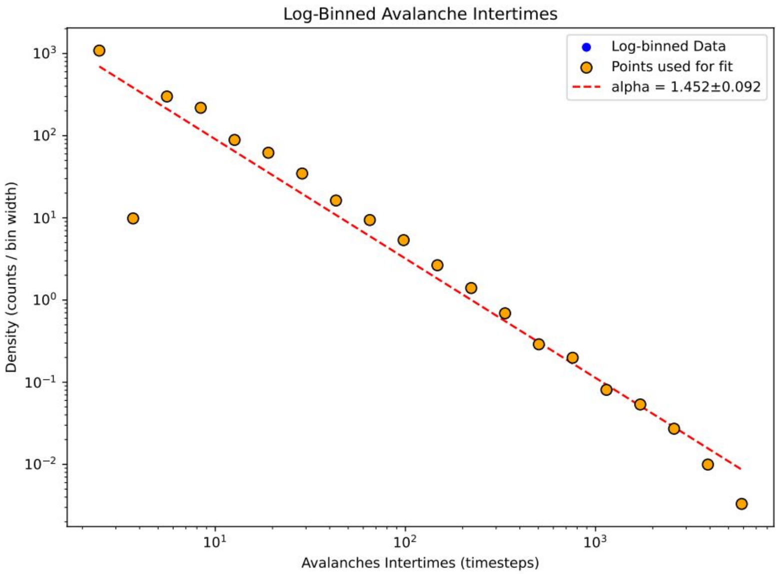
(a) Our results



(a) Bartolozzi et al. (2005)

Avalanches inter-times

Power-law distribution



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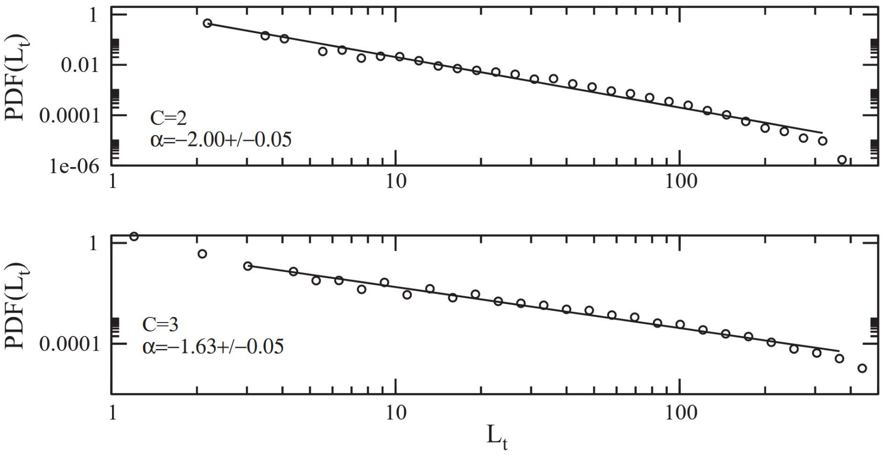
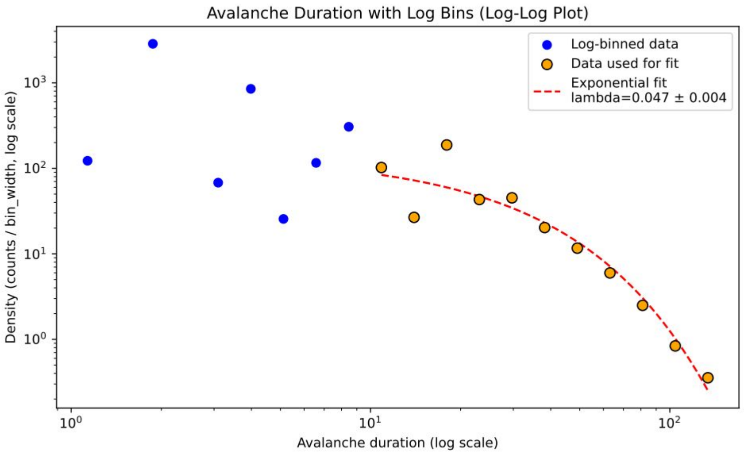


(a) Bartolozzi et al. (2005)

Avalanches durations

The fitted curve indicates an **exponential decay**.

Central Limit Theorem: avalanches durations result from the sum of many small independent / weakly correlated contributions



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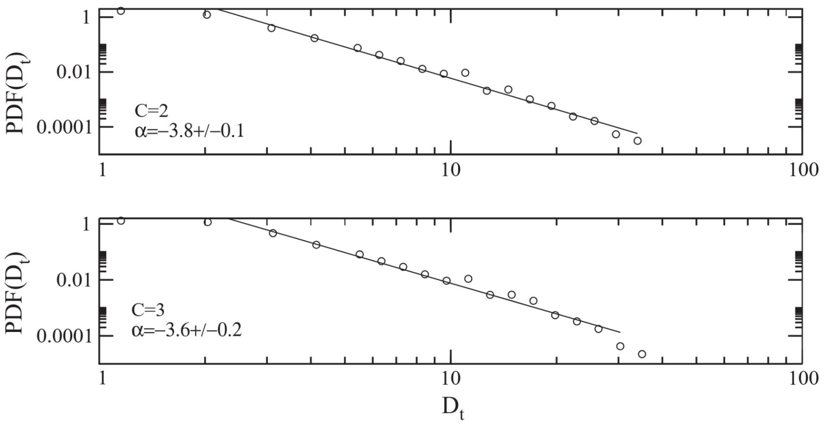

(a) Bartolozzi et al. (2005)

Discussion & Conclusion

- Our simulated market shows quasi-SOC behaviour, as in Bartolozzi et al. (2015). “Memoryless”?
- Correlations over time do not allow the system to fully self-organize into a memoryless state.

- **Future directions**:
  - fitting this model to real market data;
  - change **influence logic** between nodes, and/or modify **heterogeneity** and **composition** within network;
  - evaluate the impact of **regulations** on market dynamics, such as limits on hedge fund trading volumes.

Thank you!

References

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