HAMS and Stylized Facts in FM

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The Question

Financial markets display persistent statistical regularities.

Examples include:

- Returns are difficult to predict (little autocorrelation)
- Periods of high volatility tend to cluster
- Large price changes occur more often than predicted by a normal distribution

Standard benchmark models struggle to explain these empirical properties.

Question: Can heterogeneous expectations and adaptive behavior help explain these patterns?

Why Study Financial Markets?

Financial markets are a natural laboratory for studying economic dynamics.

- They generate large amounts of high-frequency data
- Similar statistical patterns emerge across assets, countries and time periods
- These empirical regularities provide a benchmark for theoretical models

Stylized Facts

Before building models, economists first look at the data.

Stylized facts are statistical regularities observed across different financial markets, assets and time periods.

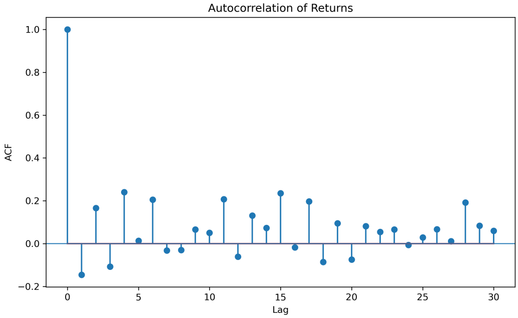
Despite differences in institutions, regulations and events, financial markets tend to display similar patterns.

These empirical regularities represent a key benchmark for theoretical models of financial markets.

Stylized Facts: Asset Returns

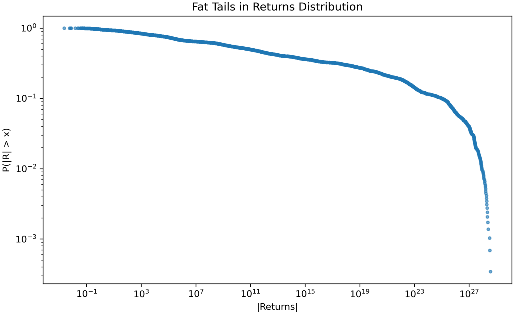
- **Absence of autocorrelation** Returns are typically not predictable using past returns. Successive price changes are approximately uncorrelated.
- **Leptokurtosis** The distribution of returns has much fatter tails than a normal distribution. Large price changes occur more often than expected under normality.
- **Gain/loss asymmetry** Large negative returns are more frequent than large positive returns (negative skewness).

Absence of Autocorrelation



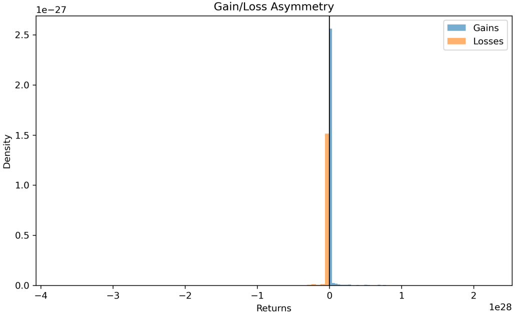
Returns typically show very low autocorrelation. Past returns provide little information about future returns.

Leptokurtosis



The distribution of returns has fatter tails than a normal distribution. Large price changes occur more frequently than predicted by normality.

Gain/Loss Asymmetry

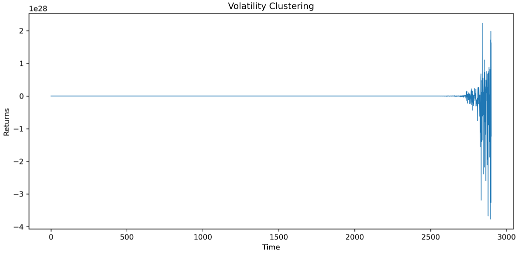


Large negative returns tend to occur more frequently than large positive returns.

Stylized Facts: Volatility

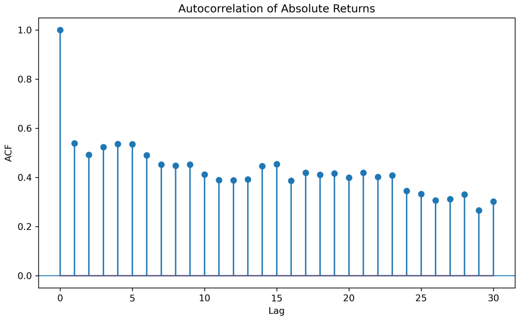
- **Volatility clustering** Periods of high volatility tend to be followed by periods of high volatility, and calm periods tend to persist.
- **Fat tails** The unconditional distribution of returns displays power-law tails. Extreme events are more frequent than predicted by a normal distribution.
- **Long memory in volatility** The autocorrelation of absolute returns decays slowly over time, suggesting persistent volatility dynamics.

Volatility Clustering



High-volatility periods tend to cluster in time.

Long Memory in Volatility



The autocorrelation of absolute returns decays slowly, indicating persistent volatility dynamics.

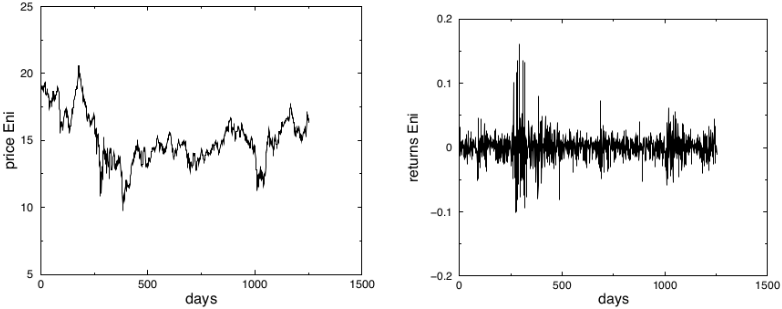


Figure: Daily time series of the ENI (left side) and ENI return (right side)

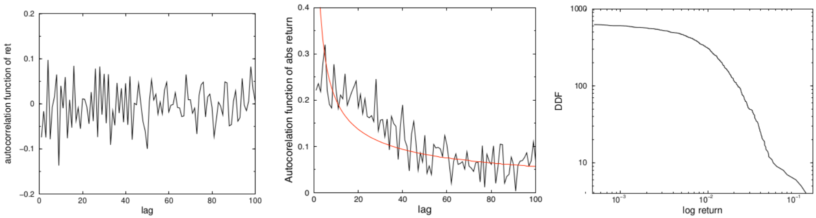


Figure: Autocorrelation function of return (left side) of the absolute value of return (middle) and decumulative distribution function of the return.

Skewness: -0.625; Kurtosis 10.192. A measure of fat tails is provided by the Hill exponent. Empirically the tail exponent is found to take values between 2 and 4. In this case H $= 3.1$. A measure of long term memory is provided by the modified R/S analysis, where the parameter β allows to discriminate between short and long term memory. If only short memory is present β converges to $1/2$ while with long memory, it converges to a value larger than $1/2$. In the case of the ENI $\beta = 0.73$.

From Stylized Facts to Models

Empirical evidence shows that financial markets display persistent statistical regularities:

- Returns are difficult to predict
- Volatility tends to cluster over time
- Extreme price changes occur more often than predicted by a normal distribution

Standard benchmark models struggle to reproduce these features.

Question: What kind of model can generate these empirical patterns?

Heterogeneous Agent Models (HAMs)

Heterogeneous Agent Models assume that financial markets are populated by agents with different expectations and strategies.

Typical types of traders include:

- Fundamentalists
- Chartists (trend followers)
- Adaptive or heuristic traders

The interaction among heterogeneous strategies may generate complex market dynamics.

First Applications

- Zeeman 1974;
- Goldman (1980);
- Frankle and Froot (1986, 1990);
- Day and Huang (1990);
- Chiarella (1992);
- Brock and Hommes (1997, 1998);
- Farmer (2002), Joshi (2002);
- and so on...

Heterogeneity

1. Group of Agents with different strategies (Fundamentalists, Chartists, Noise traders, Bias traders, Naive)

- Fundamentalists: $p^e_{t+1} = p^f$
- Adaptive: $p^e_{t+1} = wp_{t-1} + (1-w)p^e_t$
- TrendFollowing (chartist): $p^e_{t+1} = p_{t-1} + \gamma(p_{t-1} - p_{t-2})$. Weak ($\gamma = 0.4$) or Strong ($\gamma = 1.3$)
- Anchoring and Adjustment: $p^e_{t+1} = 0.5(p^f + p_{t-1}) + (p_{t-1} - p_{t-2})$

Switching Mechanism

2. Fixed quotas vs. Evolutionary switching mechanisms

   - Fixed quotas: Agents cannot change the strategy adopted
   - Variable quotas: Agents may change according to some rule

The Dealer

3. Walrasian Auctioner vs. Market Maker

- Walrasian Auctioner: $Demand = Supply$
- Market Maker: $p_{t+1} = p_t + f(ED)$

Roadmap

In the next steps we will explore how heterogeneous expectations can generate the stylized facts observed in financial markets.

- A simple HAM toy model
- Evolutionary switching and discrete choice
- The Brock–Hommes (1998) model
- Empirical validation and laboratory experiments