Topics in complexity economics

Complex Systems Summer School
July 5, 2016

J. Doyne Farmer

Mathematical Institute and

Institute for New Economic Thinking at the Oxford Martin School

External professor, Santa Fe Institute

Overview of lectures

1. Agent-based modeling of the economy: The vision, the problems, and the reality
2. A physicist's perspective on economics:
   - The perils of scientific cross-dressing, or
   - a case study in how to have an unusual career
3. Toward an evolutionary theory of technological change
   - with a few metaphysical remarks about progress

Questions Sander challenged us with

- Did science choose you or did you choose it?
- How did you end up in interdisciplinary research?
- What was your career like?
- Is it hard to get funding, did you ever feel you had to compromise on interest, subject or even integrity?
- Did being a scientist change your view on life and the world in general, and in what sense?
- How is science going to help solving the world's most pressing problems?
- What are the scientific problems you would like to solve personally, but also what would you hope could be achieved in your lifetime by the community you are part of?

Agent-based Modeling of the Economy:

The vision, the problems and the reality

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Why is economics interesting?

The economy is society's metabolism

Everything depends on it.

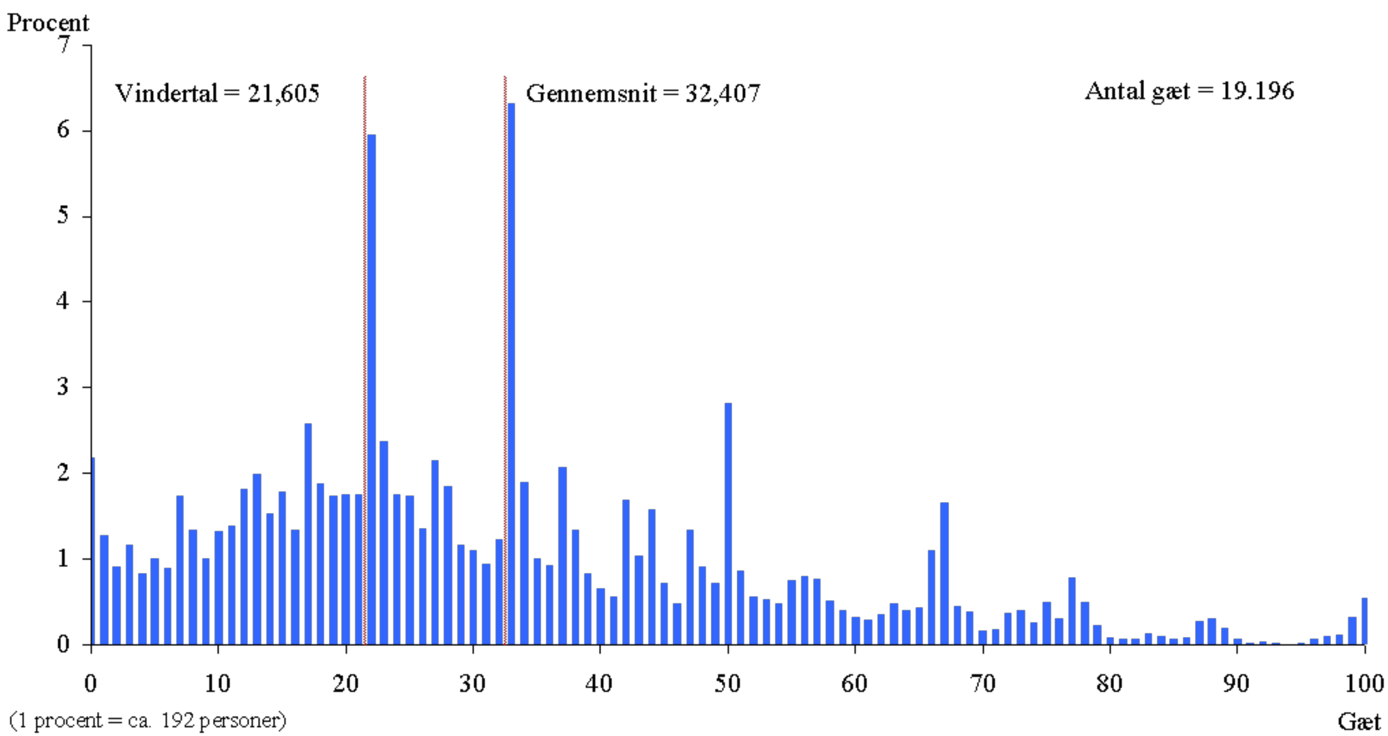
Standard template for an economic model

- Assume agents have preferences and beliefs
- Find fixed point equilibrium where agents maximize preferences according to beliefs
  - in strong form preferences are utilities and beliefs are based on rationality
  - program in economics over last 30 years has been to modify assumptions one at a time, e.g. asymmetric information, institutional constraints, only some agents rational, …

Different kinds of equilibrium

- Physical equilibrium
  - forces balance
- Thermodynamic equilibrium
  - heat flows in steady state
- Strategic equilibrium
  - agents fully consider each other’s behavior

Fordeling af gæt i "Gæt Et Tal"s første runde i september 2005



Hvis du har spørgsmål til konkurrencen er du velkommen til at kontakte os via e-mail (konkurrence@econ.ku.dk) eller på telefon 35 32 30 51.

Denne konkurrence er en del af et videnskabeligt studie under ledelse af prof. dr. Tyran.

When is equilibrium assumption justified?

- To test this use the context of game theory
- There are players who choose one of several possible actions (moves) at each turn
- Players receive payments based on the combined actions of all players
- Game is played repeatedly
- Make players learn their strategies

(Note significant pre-existing literature)

What is typical behavior?

Our approach (Galla and Farmer, PNAS 2013)

- Construct games at random (i.e. choose random payoff matrix but keep fixed throughout game)
- Try to characterize long-time behavior of games a priori.
  - analogy to Reynolds number in fluid turbulence

Intuitions

- Simple games should be easier to learn than difficult games
- From a dynamical systems point of view, there must be something special if fixed points are generically stable
  - Nash proved there is always a fixed point for a game with mixed strategies
  - But not necessarily stable

Ensemble of games

- Choose payoffs so that they are normally distributed, satisfying

$$E[\Pi_{ij}^{A}\Pi_{ji}^{B}] = \Gamma/N$$

If $\Gamma = -1$ then game is zero sum

Learning: Experience weighted attraction

- Reinforcement learning: Players learn strategies based on actions that were successful in the past.

$$x_i^\mu(t) = \frac{e^{\beta Q_i^\mu(t)}}{\sum_k e^{\beta Q_k^\mu(t)}}$$

x_i^μ = probability player μ takes action i

Q_i^μ = Attraction of player μ to action i

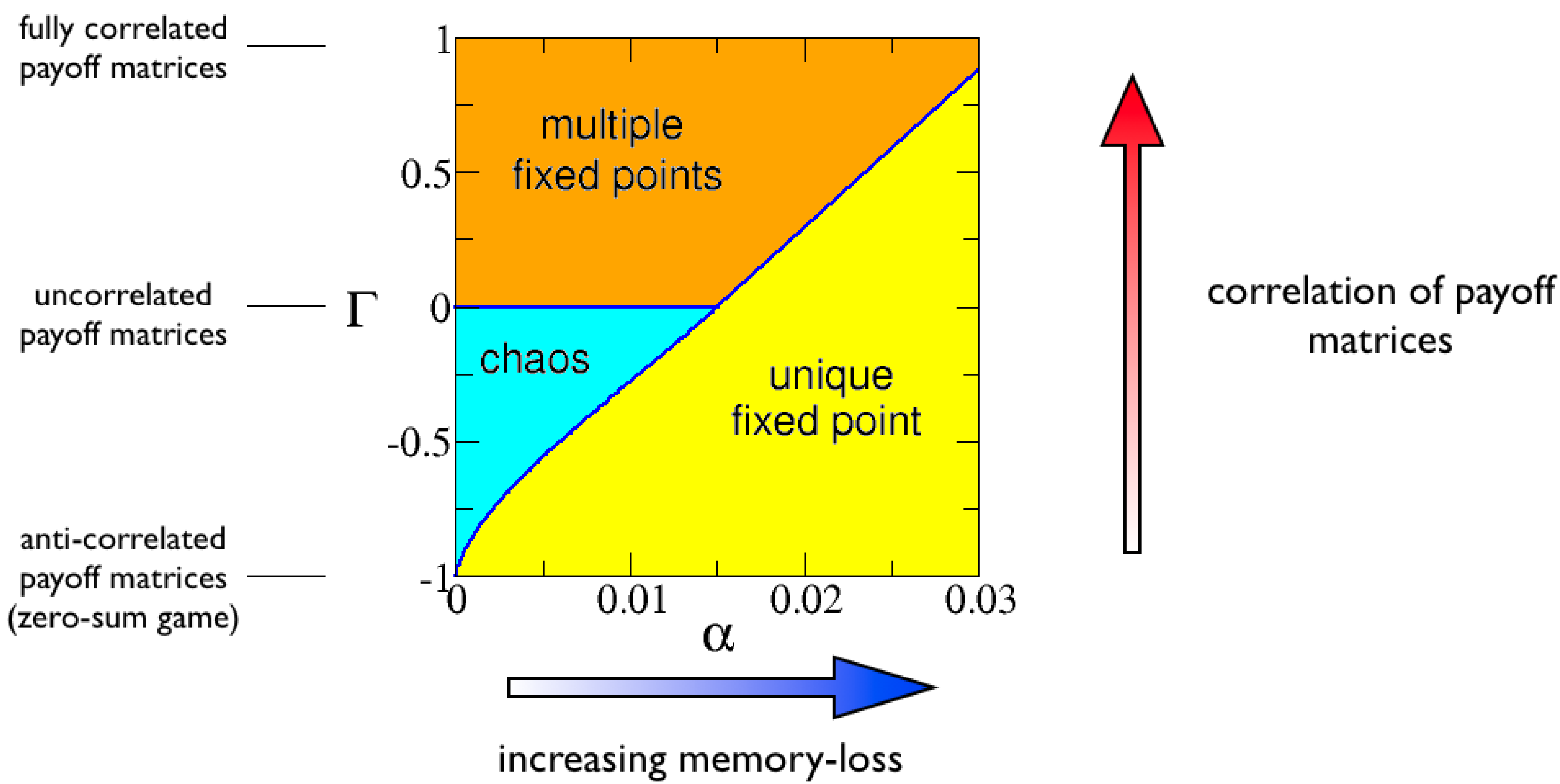
β = intensity of choice

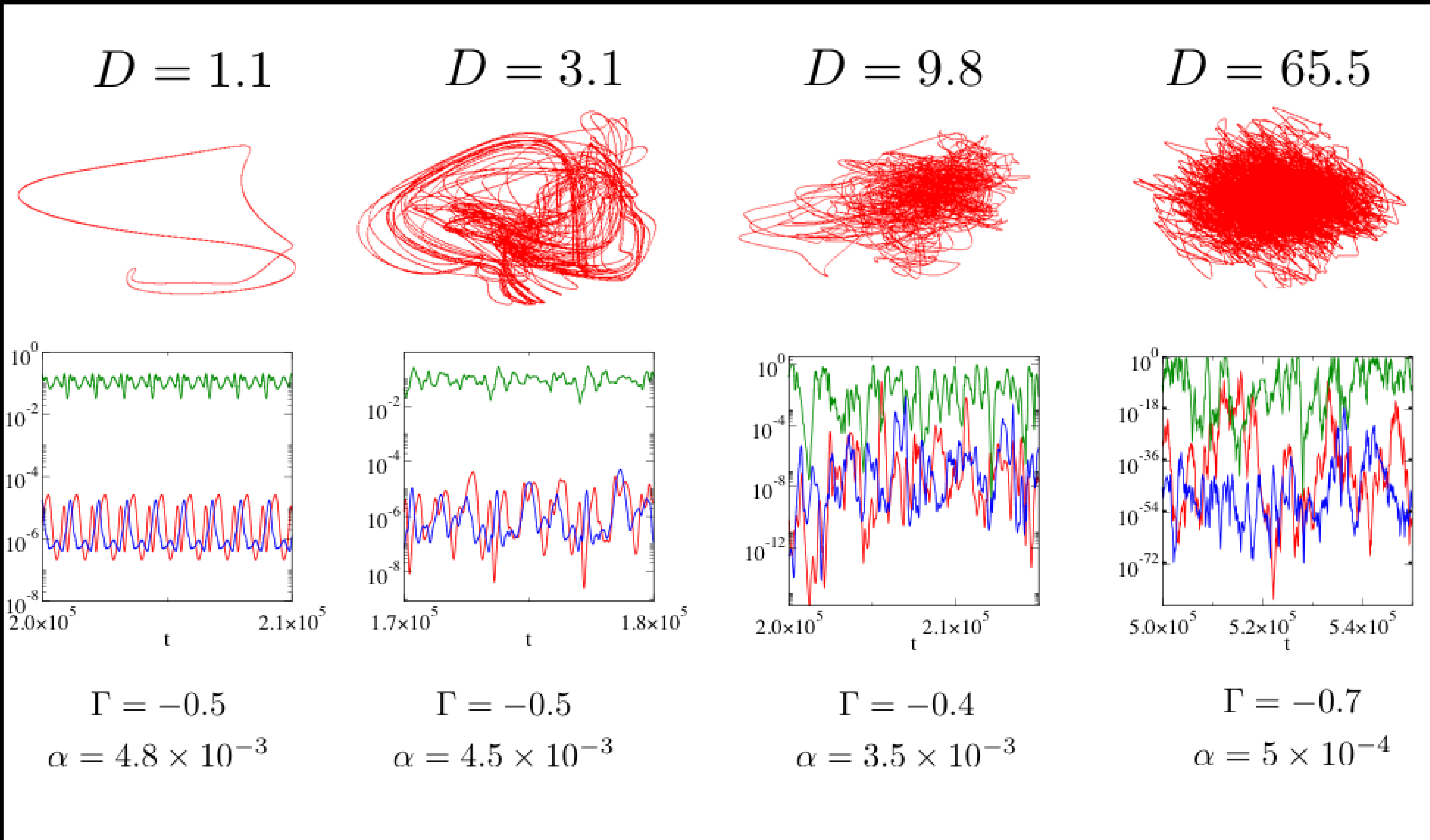
α = learning rate

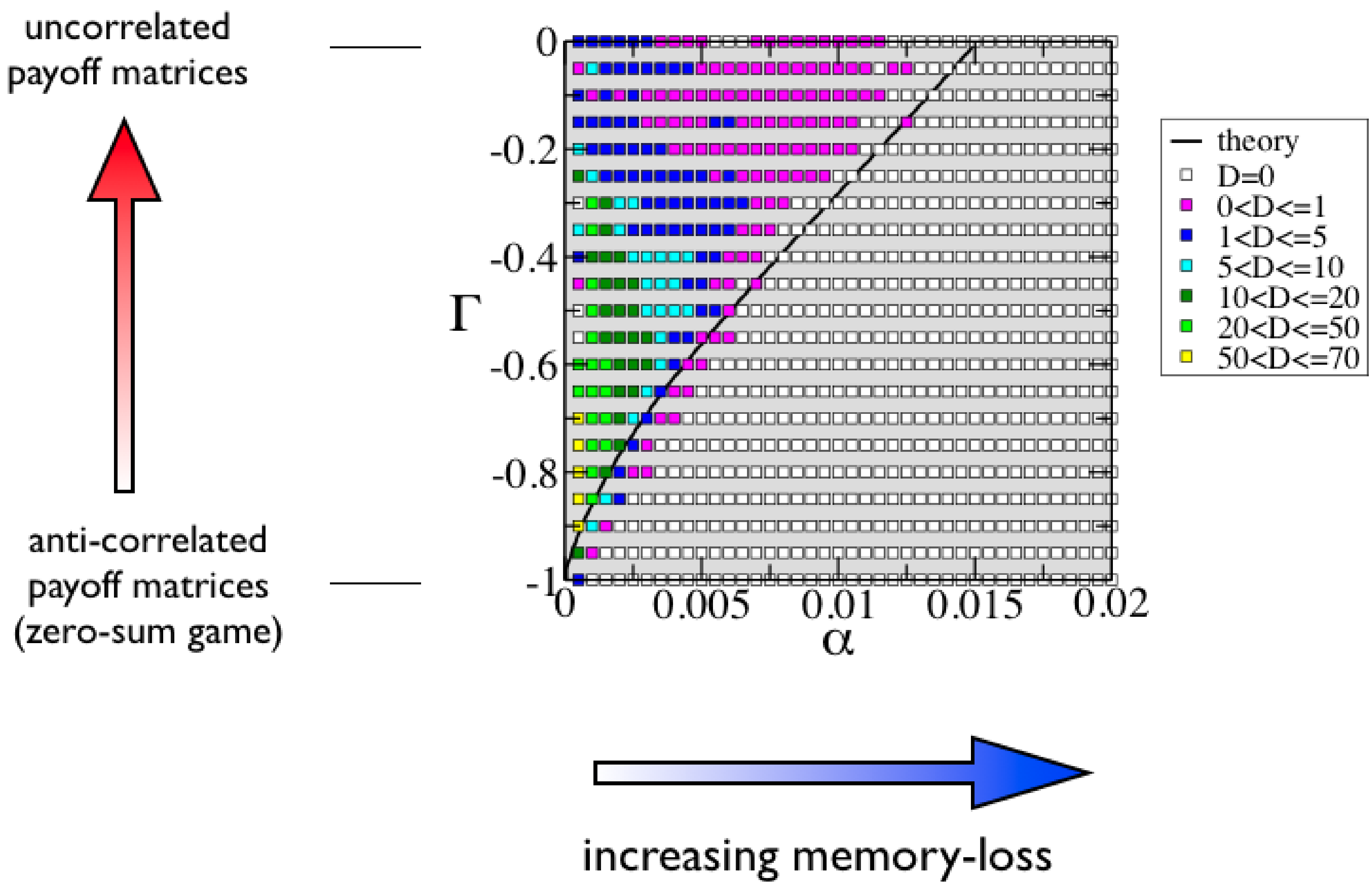
Π_{ij}^A = payoff to player A from actions i, j

$$Q_i^A(t+1) = (1-\alpha)Q_i^A(t) + \alpha \sum_j \Pi_{ij}^A x_j^B$$

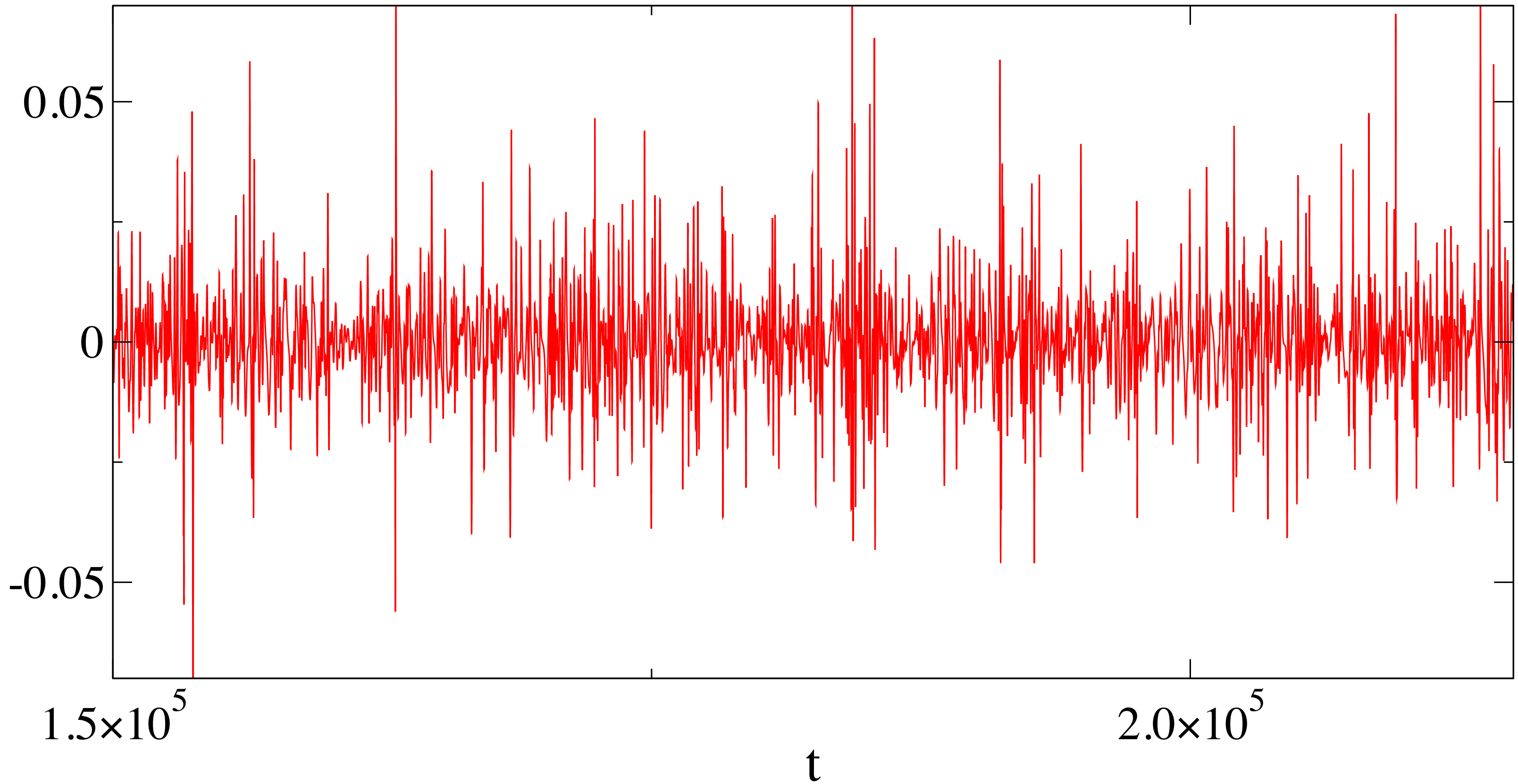
Assume enough rounds are played before updating strategy to get rid of statistical uncertainty


fully correlated
payoff matrices
uncorrelated
payoff matrices
anti-correlated
payoff matrices
(zero-sum game)
Γ
α
1
0.5
0
-0.5
-1
0
0.01
0.02
0.03
multiple
fixed points
chaos
unique
fixed point
correlation of payoff
matrices
increasing memory-loss

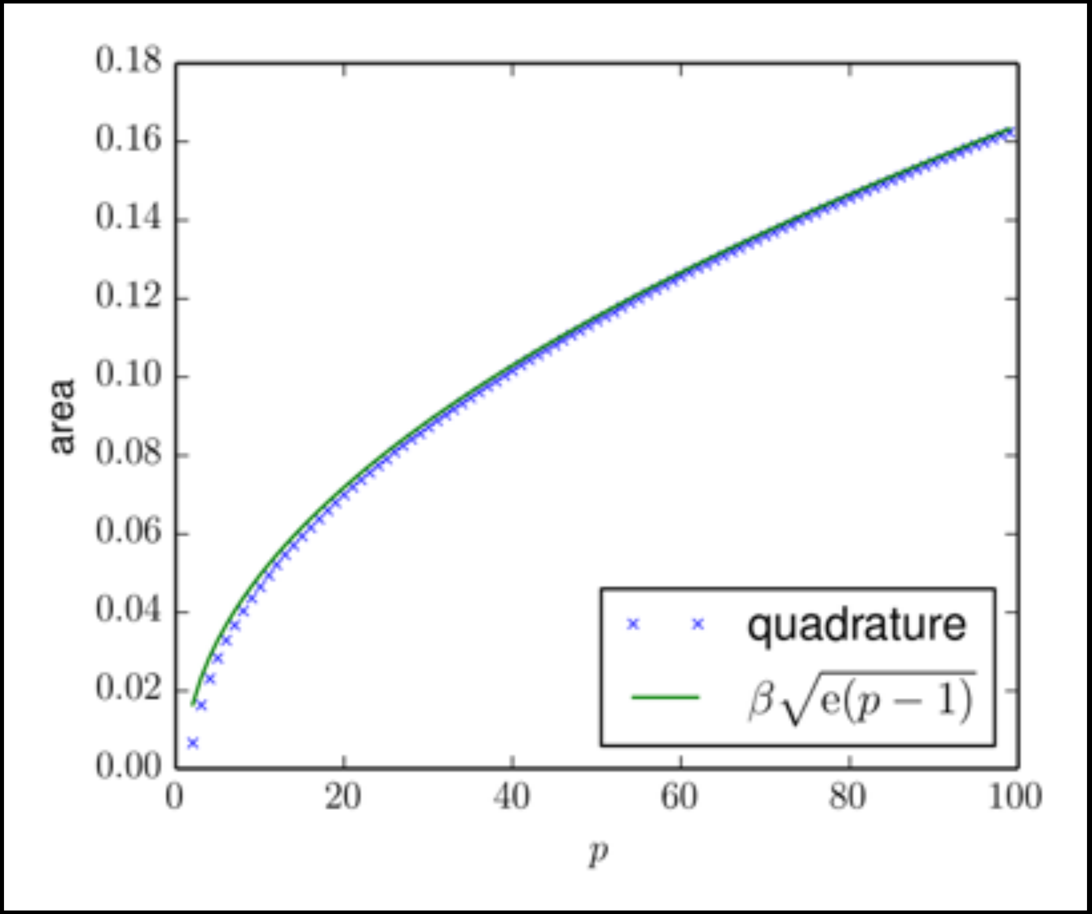

D = 1.1
10^0
10^-2
10^-4
10^-6
10^-8
2.0×10^5
2.1×10^5
t
Γ = −0.5
α = 4.8 × 10^−3
D = 3.1
10^-2
10^-4
10^-6
10^-8
1.7×10^5
1.8×10^5
t
Γ = −0.5
α = 4.5 × 10^−3
D = 9.8
10^0
10^-4
10^-8
10^-12
2.0×10^5
2.1×10^5
t
Γ = −0.4
α = 3.5 × 10^−3
D = 65.5
10^0
10^-18
10^-36
10^-54
10^-72
5.0×10^5
5.2×10^5
5.4×10^5
t
Γ = −0.7
α = 5 × 10^−4


uncorrelated payoff matrices
anti-correlated payoff matrices (zero-sum game)
increasing memory-loss
Γ
α
0
-0.2
-0.4
-0.6
-0.8
-1
0
0.005
0.01
0.015
0.02
theory
D=0
0<D<=1
1<D<=5
5<D<=10
10<D<=20
20<D<=50
50<D<=70

Change in total payoff vs. time



size of chaotic regime vs. # players



Sanders, Galla, Farmer (2016)

Caveats

- Other learning algorithms?
  - level K
  - more state information
- Is this ensemble of games representative?
- Games with few actions?
  - e.g. 2x2 games
  - (Pangallo, Sander, Galla Farmer, 2016)

Alternatives

- Making models out of equilibrium requires imposing more structure
- Models that simulate behaviors of individuals are called agent-based models; provide one of the main alternatives

What is ABM?

- Agent-based models (ABMs) are a class of computational models for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) with a view to assessing their effects on the system as a whole.

Agent-based models

- In a sense all economics models are agent-based models
- ABMs are *computational* models that explicitly model the micro states of individual agents or heterogeneous groups of agents.

Computation has revolutionized physical and natural science

- Makes it possible to study nonlinear dynamics and complex systems.
  - Fermi, Pasta Ulam
  - non-elephant animals
  - Most important driver of progress in last 50 years.
- Has this happened in economics and social science as it has in other fields? If not why?

Two examples of simple, qualitative agent-based models

Systemic risk

- Systemic risk in financial markets occurs when activities of individual agents cause unintended consequences due to collective interactions.
  - microprudential vs. macroprudential regulation
  - often caused by microprudential risk control
- Channels of contagion in financial markets:
  - networks of counterparty exposures (lending)
  - overlapping portfolios (common assets)
  - others, e.g. conversation, mass media, …

Key factors

- Dynamic effects
  - dynamic risk control, herding, cause contagion through market impact
- Network effects
  - connectedness to systemically risky institutions
  - connections can be via loans or common assets
  - both inter and intra firm channels of contagion
- Ecological effects
  - shifts in the composition of investor strategies
  - combines above, long and short term dynamics

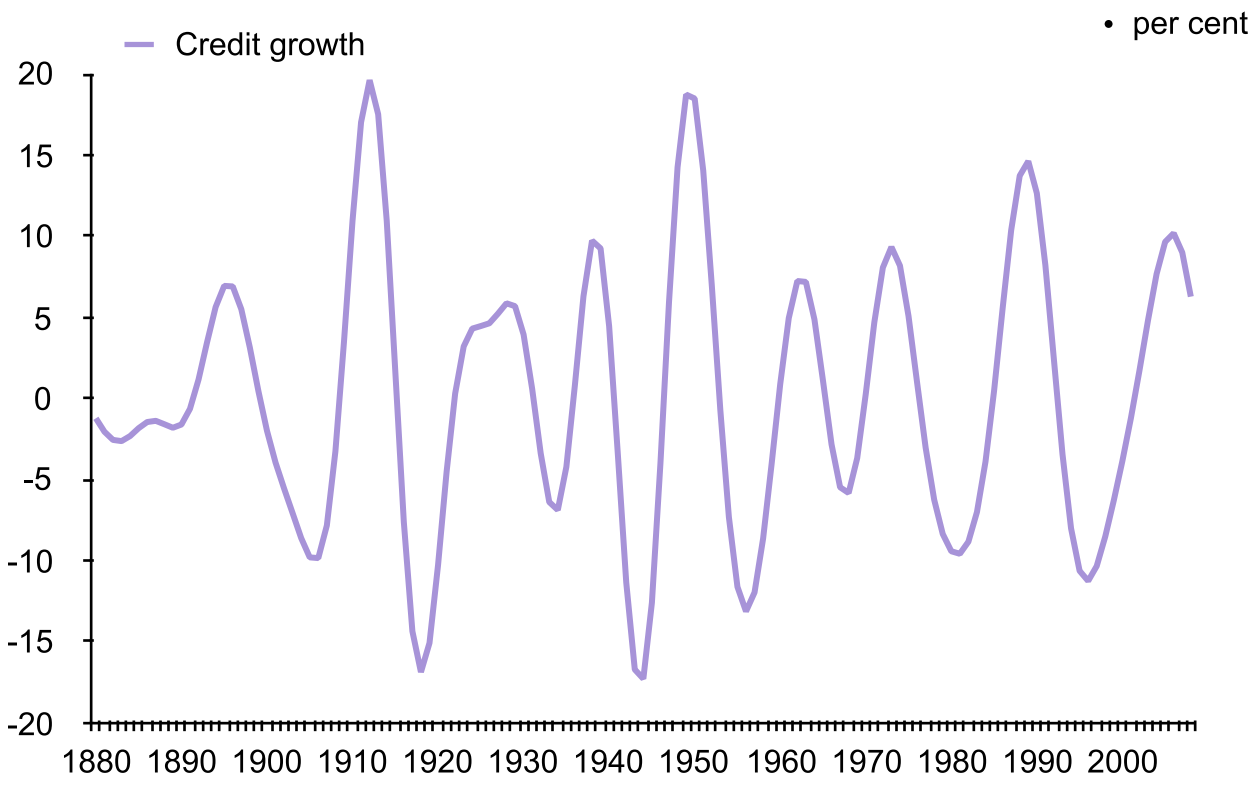
Microprudential/macroprudential tradeoff

- Microprudential regulation
  - Individual institutions minimize their own risks, without regard to how others behaving similarly might affect the market
- Macroprudential regulation
  - Concerned with systemic effects

Leverage cycles

- One of the most important examples of the dynamics of systemic risk.
- Minsky: During calm times leverage goes up due to competition for returns. With high leverage negative shocks are amplified by leverage, which triggers a crash
- Geanakoplos: Heterogenous investors, optimists use more leverage, bad news is amplified

Credit Cycles



- Source: Bank calculations

Causes of leverage cycles

- Minsky: During calm times leverage does up due to competition for returns. With high leverage negative shocks are amplified by leverage, which triggers a crash
- Geanakoplos: Heterogenous investors, optimists use more leverage, bad news is amplified

Literature on leverage cycles

- Minsky (1970s)
- Gennotte and Leland (1990)
- Danielsson et al (2001)
- Geanakoplos (2003, 2010)
- Estrella (2004)
- Danielsson, Shin and Zigrand (2004, 2010)
- Fostel and Geanakoplos (2008)
- Adrian and Shin (2008, 2014)
- Brunnermeier and Pedersen (2008)
- Thurner, Farmer and Geanakoplos (2010)
- Gorton and Metrick (2010)
- Tasca and Battiston (2010)
- Adrian, Colla and Shin (2012)
- Adrian & Boyarchenko (2012,2013)
- Corsi, Marmi and Lillo (2013)
- Poledna, Thurner, Farmer and Geanakoplos (2014)
- Caccioli, Shrestha, Moore, Farmer (2014)
- Aymanns and Farmer (2014)

Key fact

For passive investor with leverage > 1:

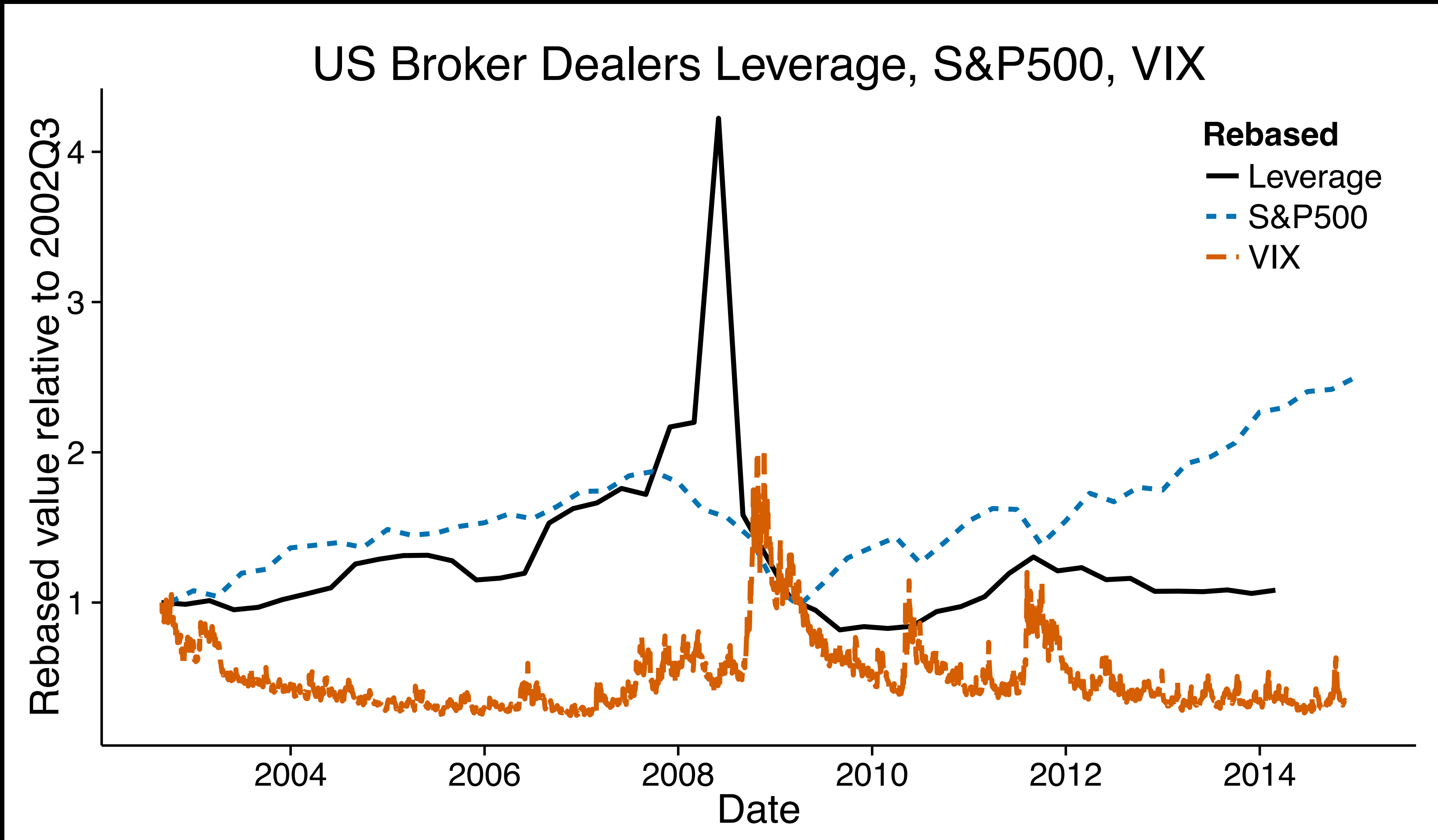
- When prices drop leverage goes up
- When prices rise leverage goes down

Reason:

Leverage = Risky assets/(Assets - liabilities)

If leverage > 1, when assets decrease in value, denominator is smaller, so affected more than numerator

Cause of Great Moderation + crisis?



Leverage targeting

- Assume bank has a leverage target $\bar{\lambda}$
- If current leverage λ' under leverage target, borrows $\Delta\mathcal{B}$ and buys $\Delta\mathcal{B}$ of asset
- If over leverage target, sells $\Delta\mathcal{B}$ and pays back loan

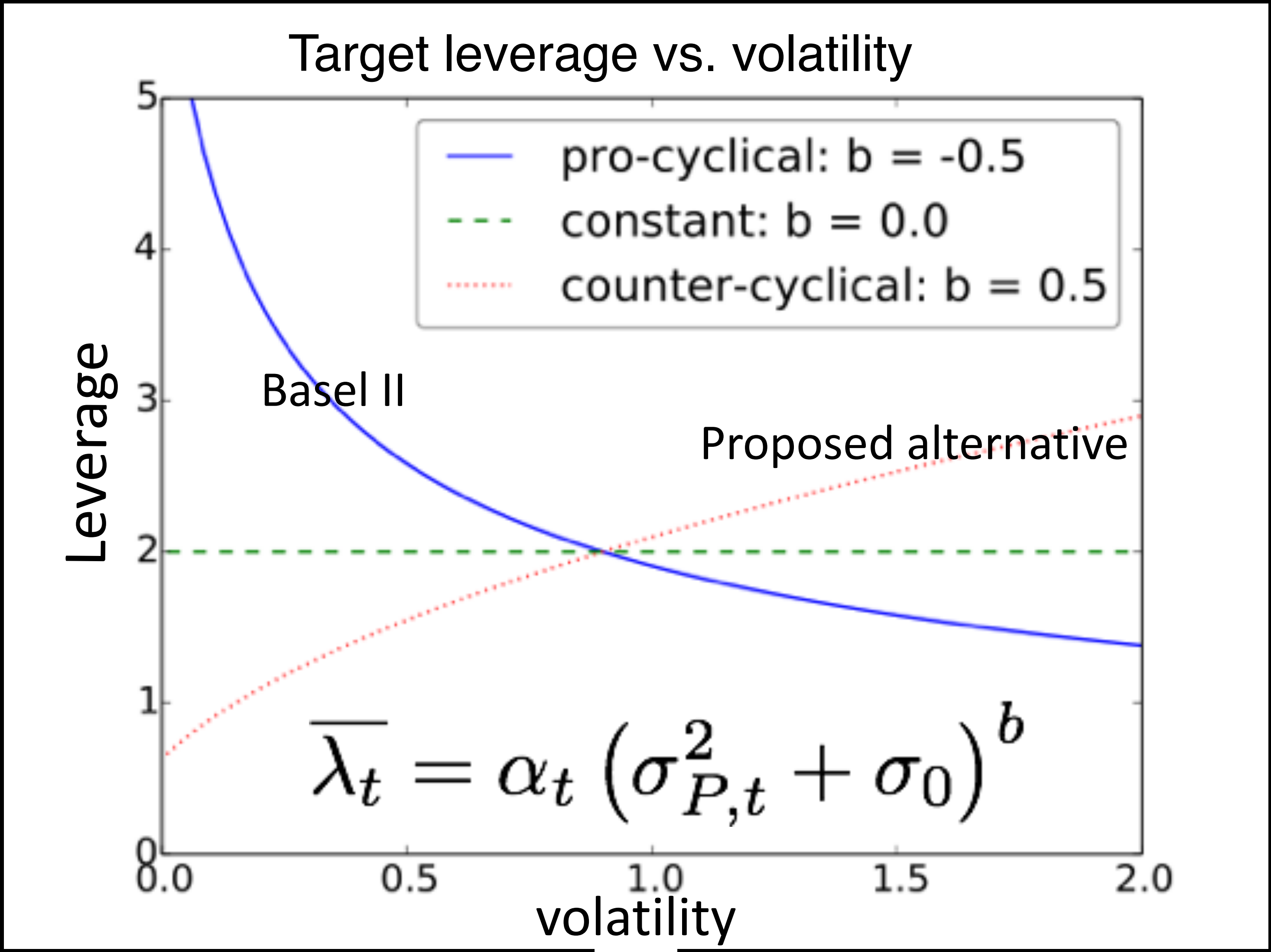
$$\lambda' = \frac{A(t)}{A(t)-\mathcal{L}(t)} \qquad \bar{\lambda} = \frac{A(t)+\Delta\mathcal{B}}{A(t)-\mathcal{L}(t)}$$

Bank trades with fundamentalist noise trader = passive investor who holds a fraction of asset; fraction driven by exogenous noise term

Commercial banks vs. investment banks

- Adrian and Shin: Commercial banks use constant leverage targets, investment banks use procyclical leverage targets.
- *Procyclical* means that leverage goes up when prices go up. *Countercyclical* means the opposite.
- Volatility and prices are negatively correlated. We will define the cyclicality of policies in terms of response to volatility, i.e. a *procyclical policy* is one that increases leverage when volatility decreases.
- My personal experience: face value -> D.S.D. -> VaR

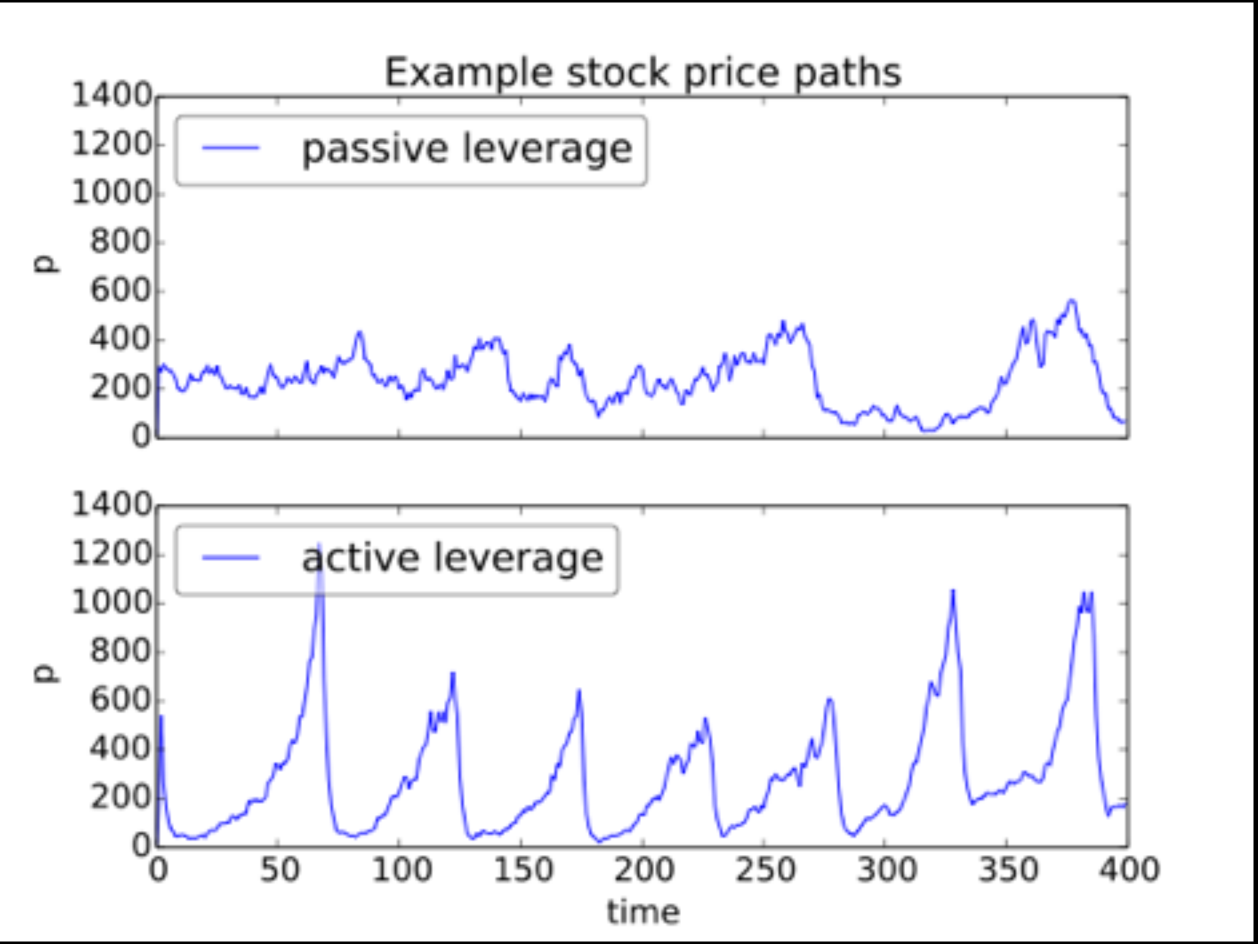
Risk management policy



Stability?

- Leverage targeting is destabilizing
  - if prices drop, leverage goes up and banks sell
  - if prices rise, leverage goes down and banks buy
- Mark-to-market accounting exaggerates feedback
- Must have unleveraged fundamental traders to stabilize markets

Agent-based model of interacting banks



Simplify to get essence

(Dynamics of the leverage cycle, Aymanns and Farmer, 2015)

- One bank, one risky asset + cash
- Three assumptions:
  - Exponential moving average of historical volatility used to estimate expected volatility
  - Basel II risk management rule
  - Simple price formation rule: Increasing leverage target implies buying => price of asset rises

Two dimensional model

$$p(t) = \overline{\lambda}(t)E$$

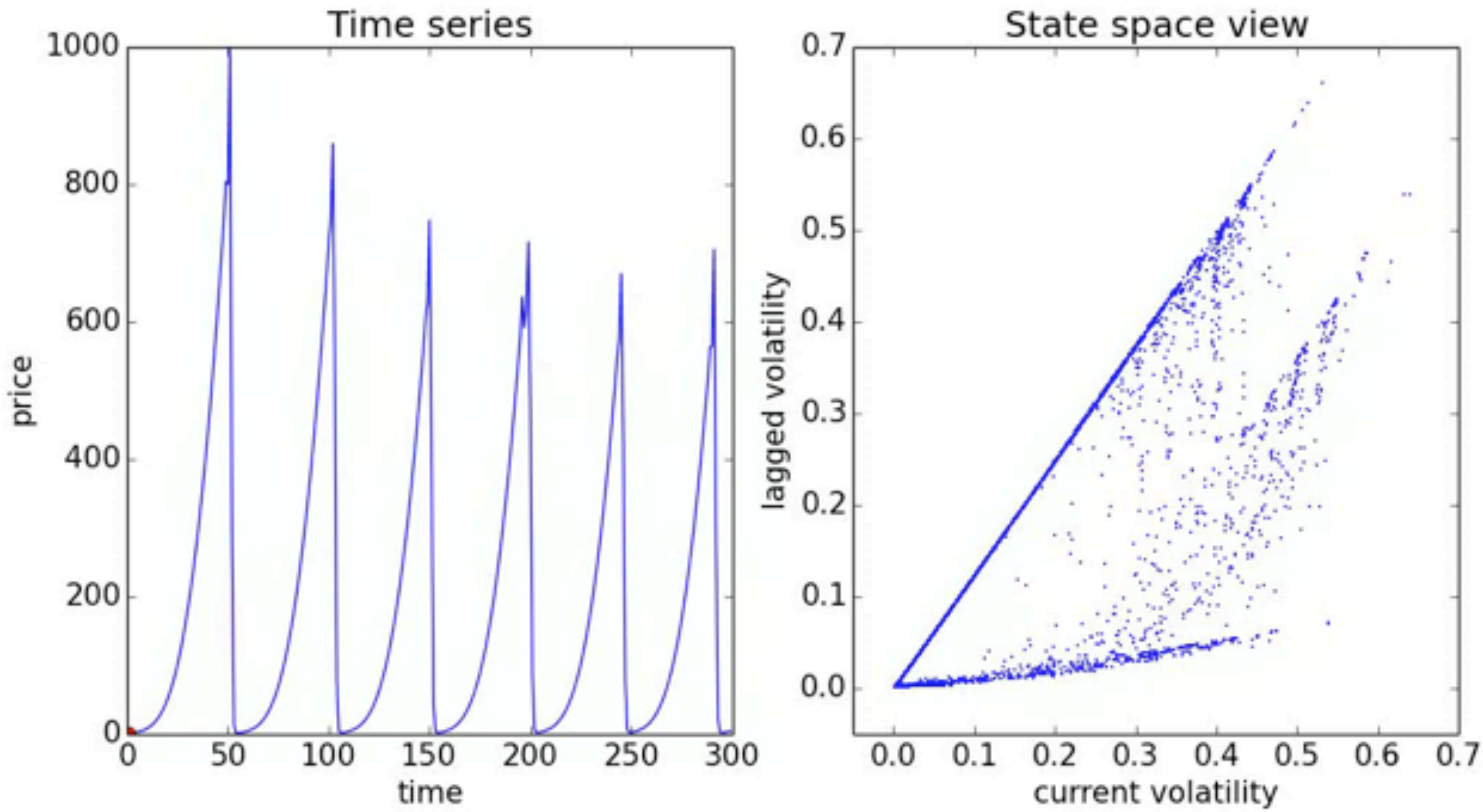
$$\sigma^2(t+1) = (1-\delta)\sigma^2(t) + \delta\left(\log\left(\frac{p(t)}{p(t-1)}\right)\right)^2,$$

$$\overline{\lambda}(t) = \alpha\left(\sigma^2(t) + \sigma_0\right)^b.$$

With sigma_0 = 0 and b = -1/2:

$$z_1(t+1) = (1-\delta)z_1(t) + \frac{\delta}{4}\left(\log\left(\frac{z_2(t)}{z_1(t)}\right)\right)^2,$$

$$z_2(t+1) = z_1(t)$$

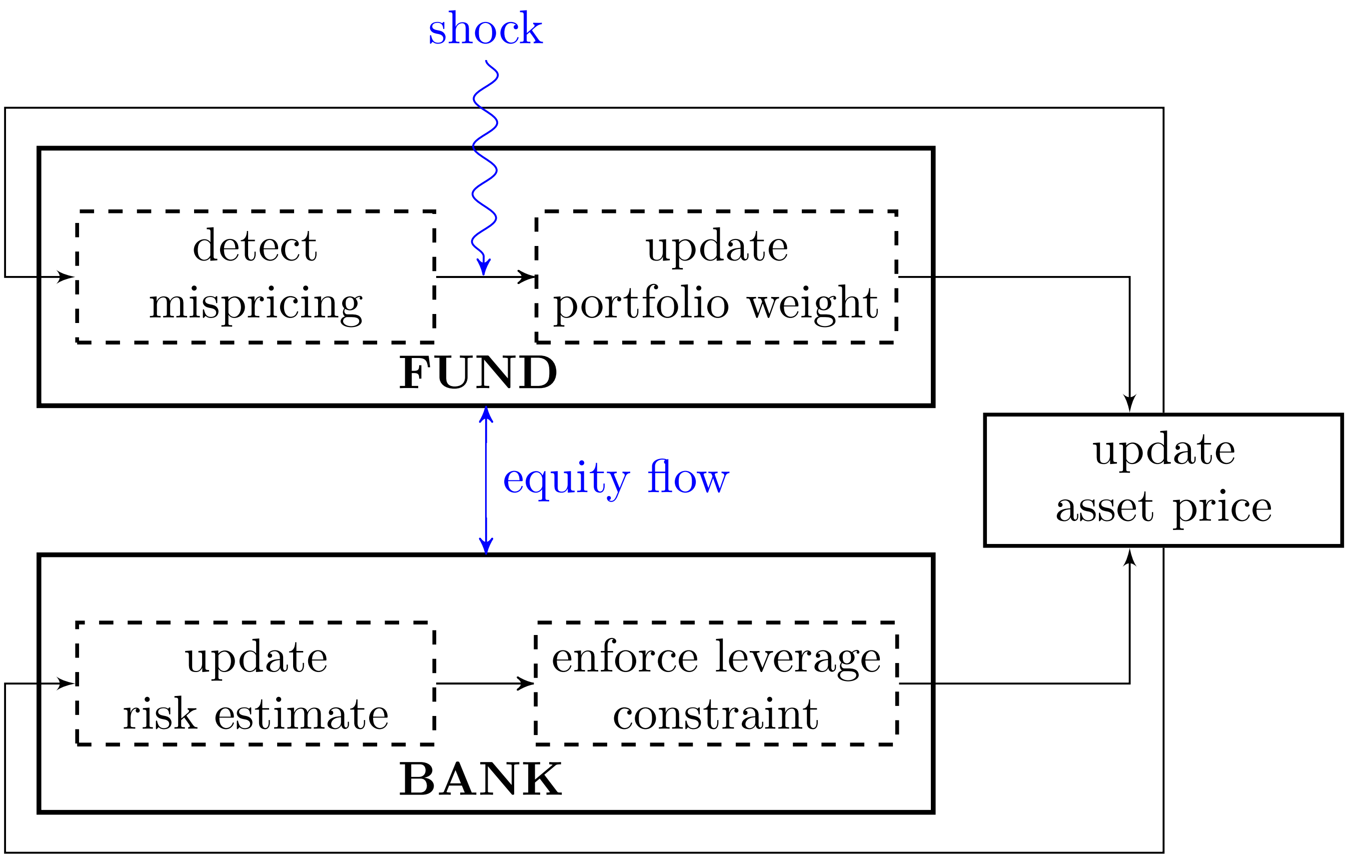


Time series
price
time
1000
800
600
400
200
0
50
100
150
200
250
300
State space view
lagged volatility
current volatility
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

More realistic model

(Aymanns, Caccioli, Farmer, Tan, 2016)

- One bank, one asset
- Key additional ingredient: “Noise trader” (unleveraged fundamentalist) that trades with bank
- Trading frequency of fundamentalist follows an exogenous GARCH process
- Well-defined continuous time limit



shock
detect
mispricing
update
portfolio weight
FUND
equity flow
update
asset price
update
risk estimate
enforce leverage
constraint
BANK

(1) Perceived Risk: $\sigma^2(t+\tau) = (1-\tau\delta)\sigma^2(t) + \tau\delta\left(\log\left[\frac{p(t)}{p'(t)}\right]\frac{t_{\mathrm{VaR}}}{\tau}\right)^2,$

(2) Fund investment: $w_F(t+\tau) = w_F(t) + \frac{w_F(t)}{p(t)}\left(\tau\rho(\mu - p(t)) + \sqrt{\tau}s\xi(t)\right),$

(3) Price: $p(t+\tau) = \frac{w_B(c(t)+\Delta B(t)) + w_F(t+\tau)c_F(t)}{1 - w_B n(t) - (1-n(t))w_F(t+\tau)},$

(4) Ownership: $n(t+\tau) = (w_B(n(t)p(t+\tau) + c(t) + \Delta B(t)))/p(t+\tau),$

(5) Liabilities: $L(t+\tau) = L(t) + \Delta B(t),$

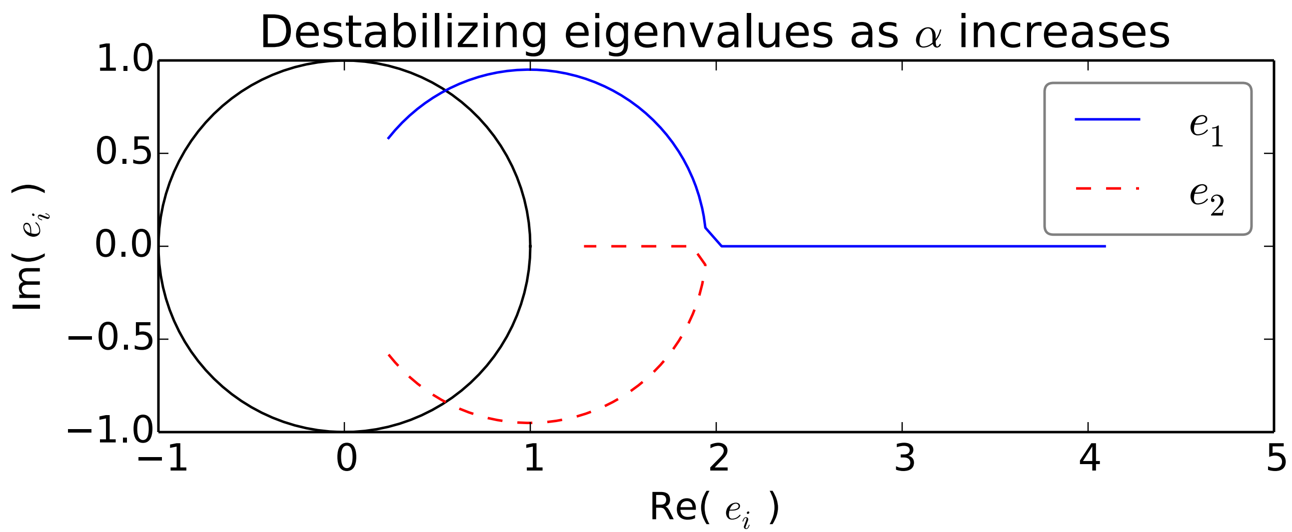
(6) Lagged price: $p'(t+\tau) = p(t).$

$$\Delta B(t) = \tau\theta(\overline{\lambda}(t)(A(t) - L(t)) - A(t))$$

Key parameters

- alpha — controls risk individual agents are willing to bear. alpha larger => more leverage
- b — determines whether leverage regulation is procyclical or countercyclical
  - procyclical: leverage drops when vol rises
  - countercyclical: leverage drops when vol drops

Linear stability analysis



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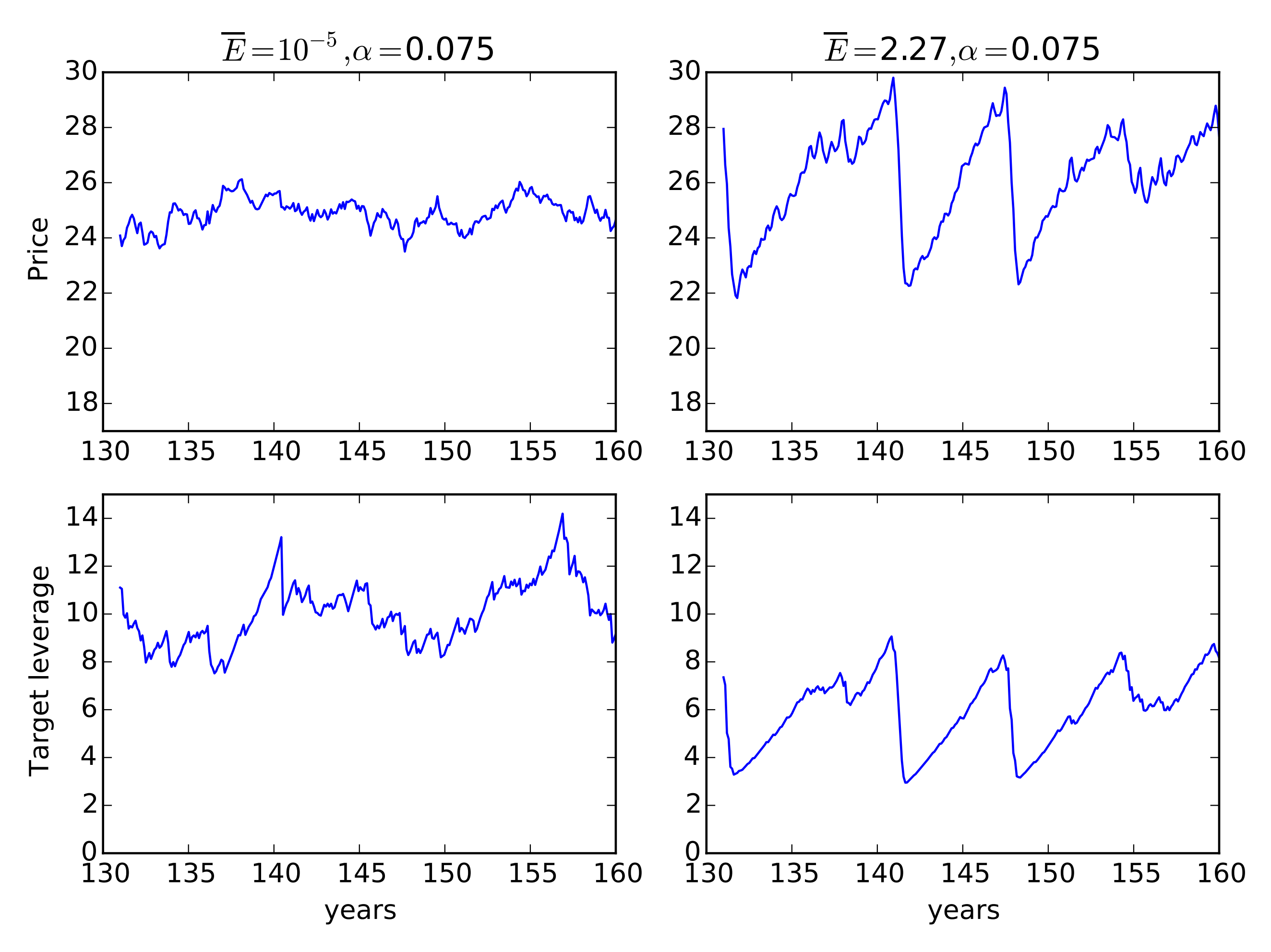
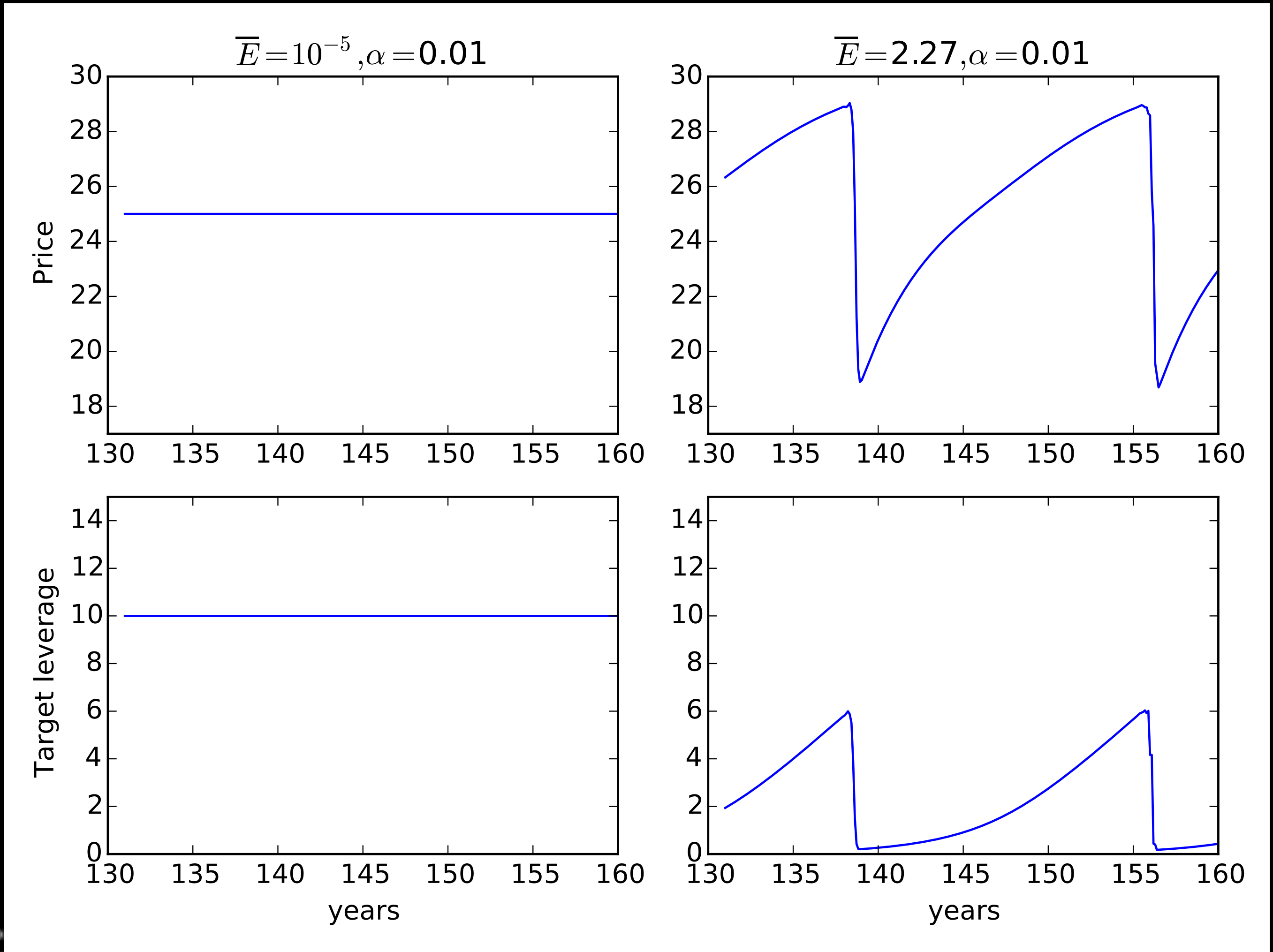
Time series with noise

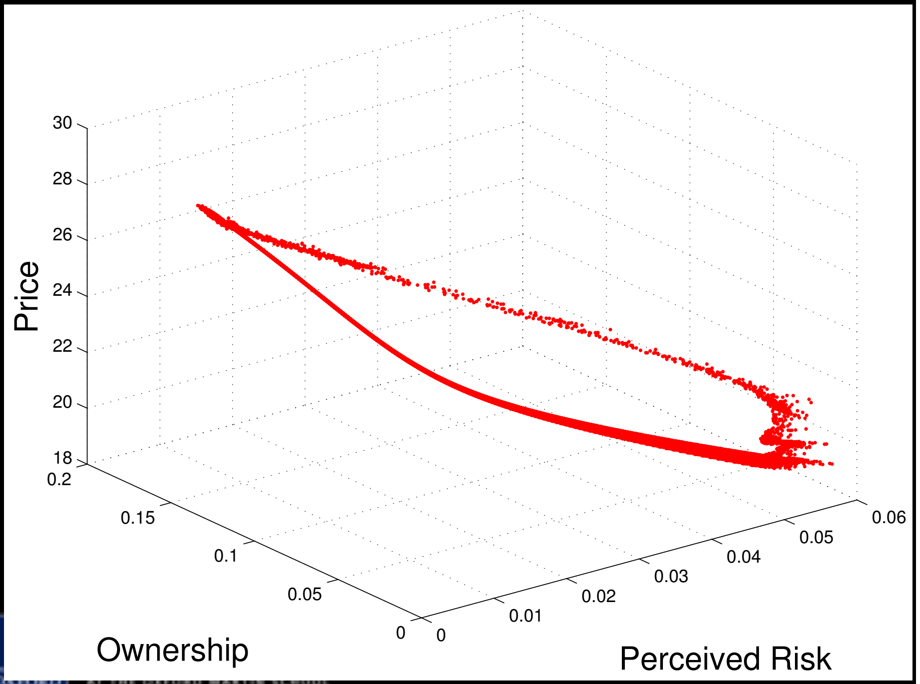


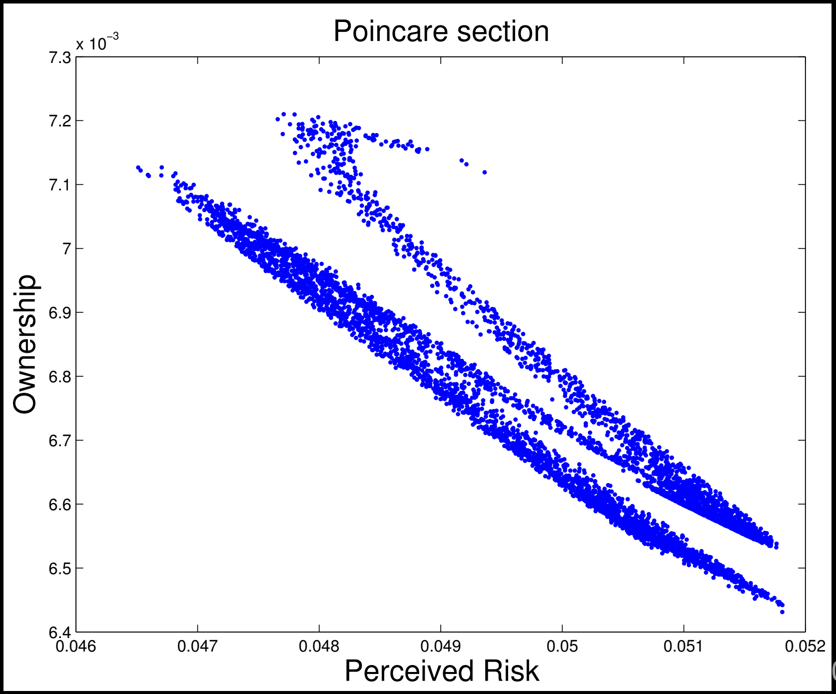
Time series without noise

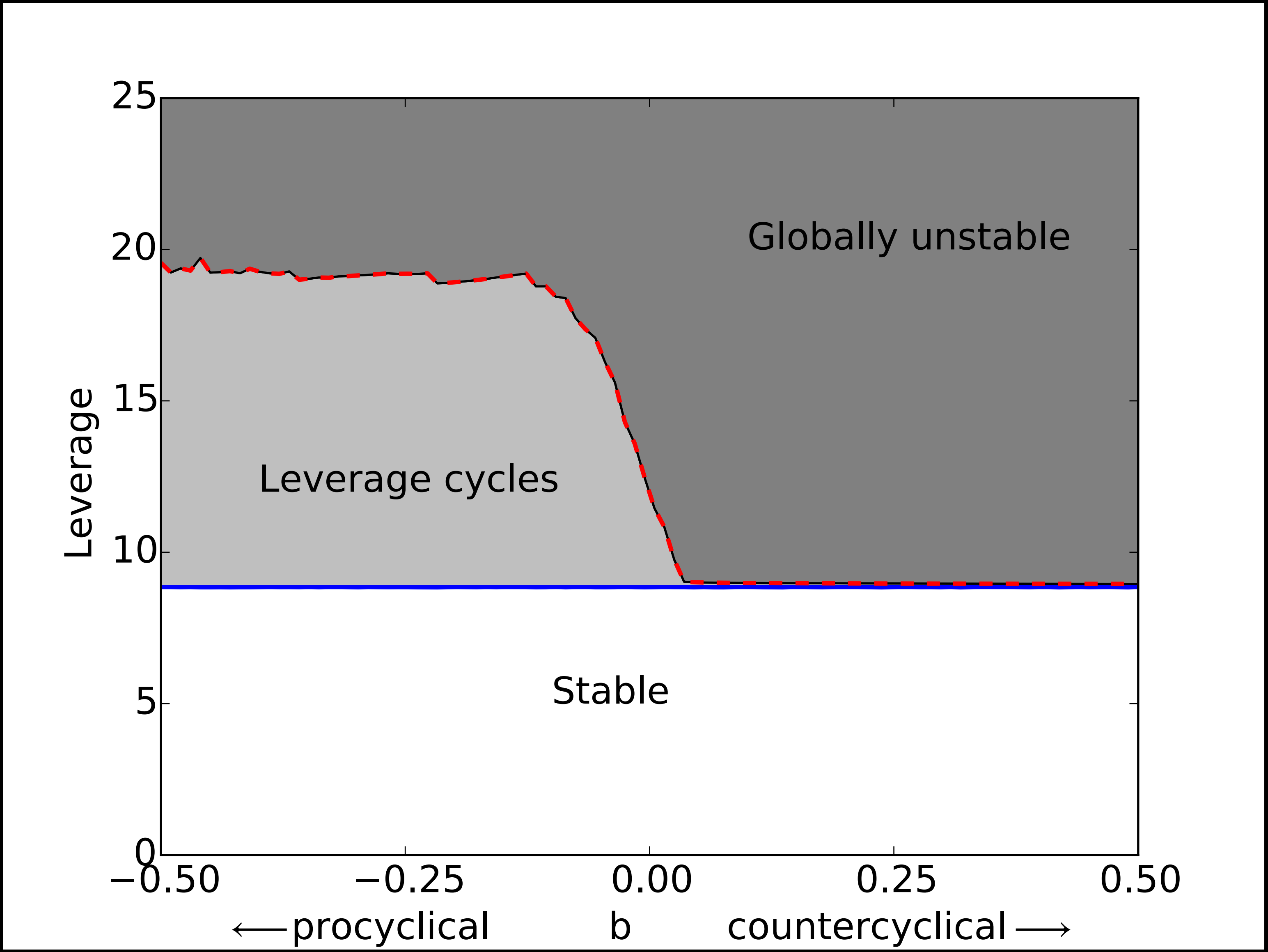


Basel strange attractor

- Flucutations are endogenously driven — do not require any noisy inputs.



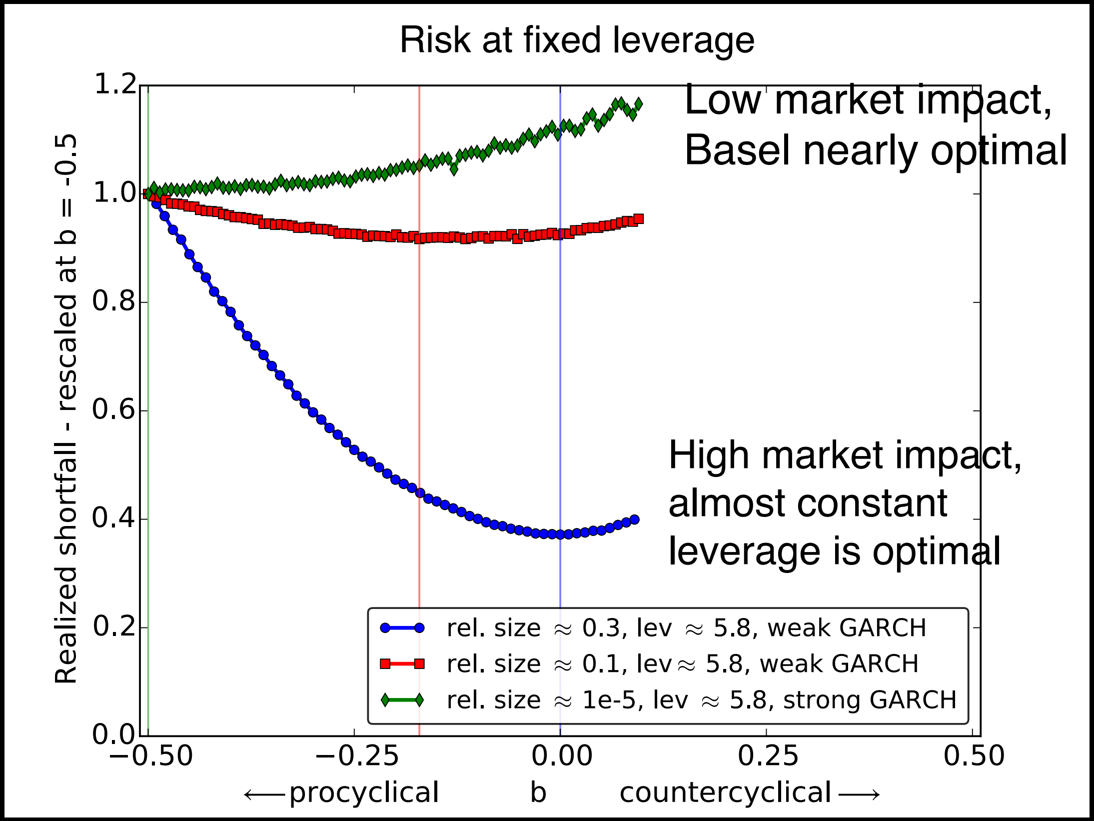




25
20
15
10
5
0
Leverage
Globally unstable
Leverage cycles
Stable
−0.50
−0.25
0.00
0.25
0.50
⟵ procyclical
b
countercyclical ⟶

Optimal policy depends on market impact of banking sector

- Low market impact: Basel optimal
- High market impact: constant leverage
- Microprudential vs. macroprudential regulation



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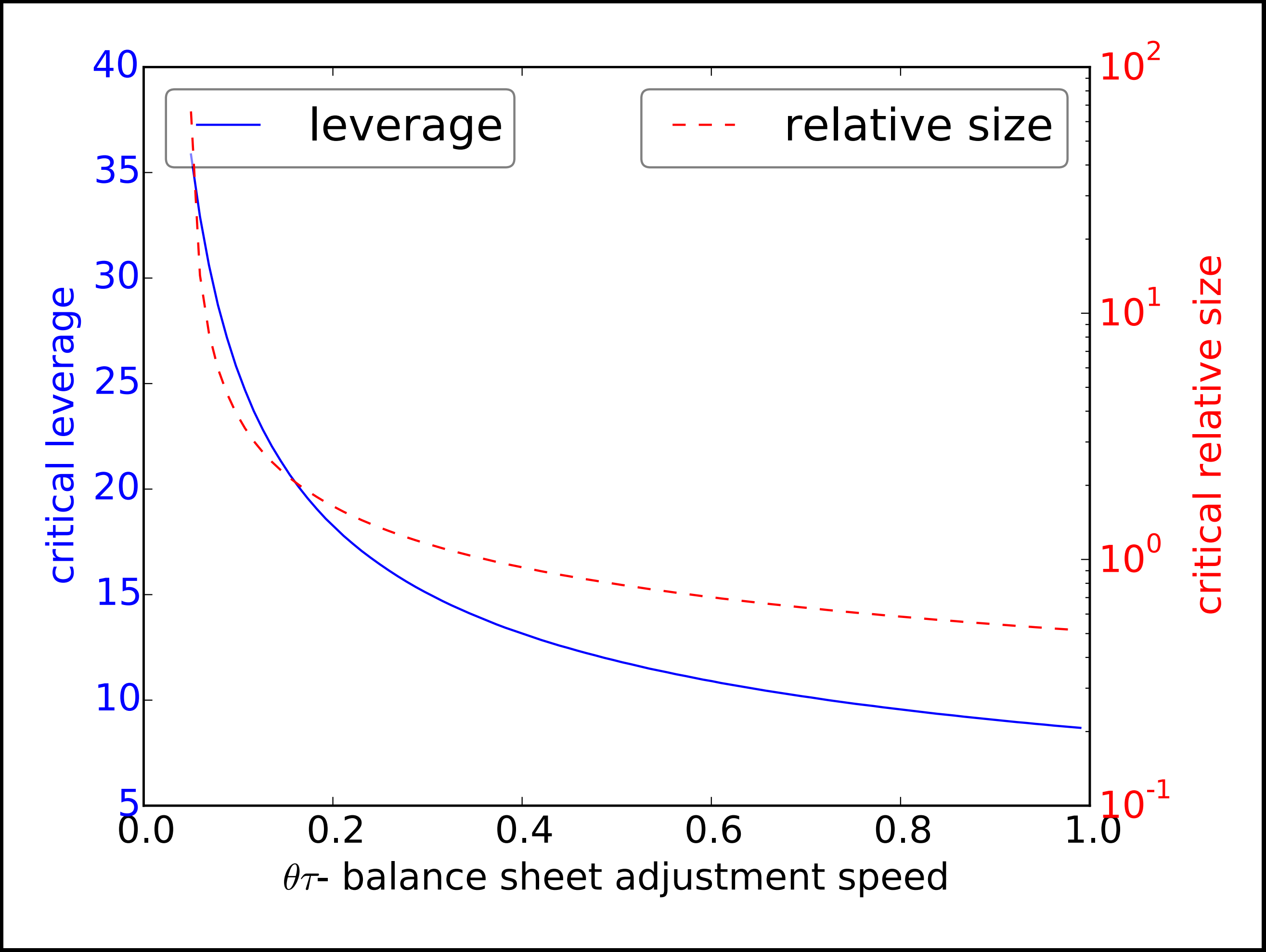
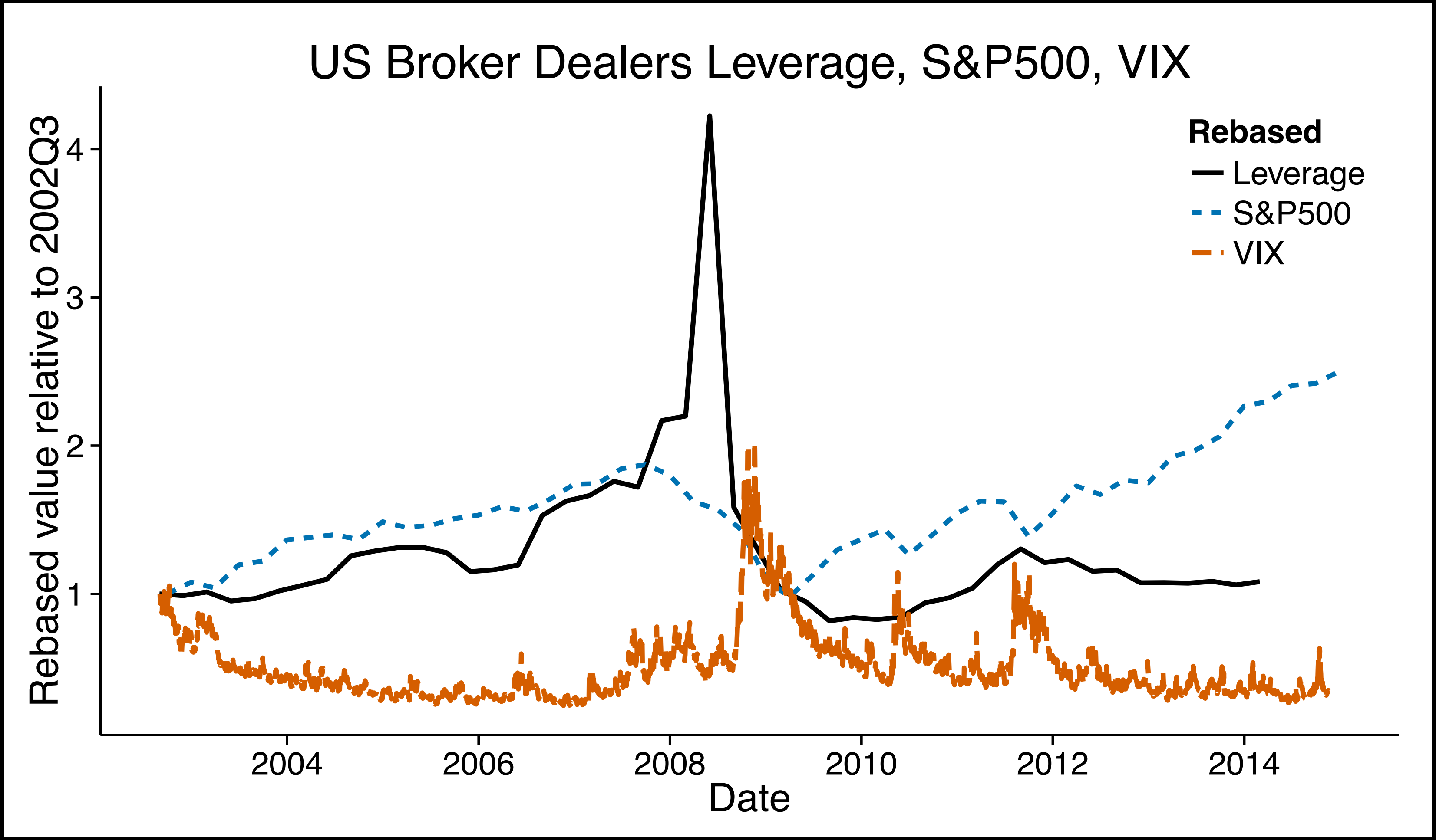
Slower adjustment stabilizes dynamics



Policy recommendation on leverage

- Know where threshold is!
  - Leave a large margin of error
- Best policy depends on size of banking sector
  - when banking sector larger, leverage must go down
  - limits must change sufficiently slowly (compromise between microprudential and macroprudential risk)
  - need carefully designed countercyclical buffers

Cause of Great Moderation + crisis?



What causes extreme risk in financial markets?

- Empirical fact: Price returns have power law tails -- essential for risk control.
- Standard explanation:
  - exogenous information arrival
- Explanation by heterodox economists using agent-based modeling:
  - trend followers + value investors (SFI stock market, LeBaron, Brock & Hommes, Lux & Marchesi, ...)
  - Key difference: Extreme events generated endogenously!

Largest S&P index moves 1946-87

(Cutler, Poterba, Summers 1989)

Rank	Date	%	NY Times explanation
1	Oct 19, 1987	-20.5	Worry over dollar decline and rate deficit Fear of US not supporting dollar
2	Oct 21, 1987	9.1	Interest rates continue to fall Deficit talks in Washington Bargain hunting
3	Oct 26, 1987	-8.3	Fear of budget deficits Margins calls Reaction to falling foreign stocks
4	Sep 3, 1946	-6.7	"No basic reason for the assault on prices"
5	May 28, 1962	-6.7	Kennedy forces rollback of steel price hike
6	Sep 26, 1955	-6.6	Eisenhower suffers heart attack
7	Jun 26, 1950	-5.4	Outbreak of Korean War
8	Oct 20, 1987	5.3	Investors looking for quality stocks
9	Sep 9, 1946	-5.2	Labor unrest in maritime and trucking
10	Oct 16, 1987	-5.2	Fear of trade deficit Fear of higher interest rates Tension with Iran
11	May 27, 1970	5.0	Rumors of change in economic policy "stock surge happened for no fundamental reasons"
12	Sep 11, 1986	-4.8	Foreign governments refuse to lower interest rates Crackdown on triple witching announced

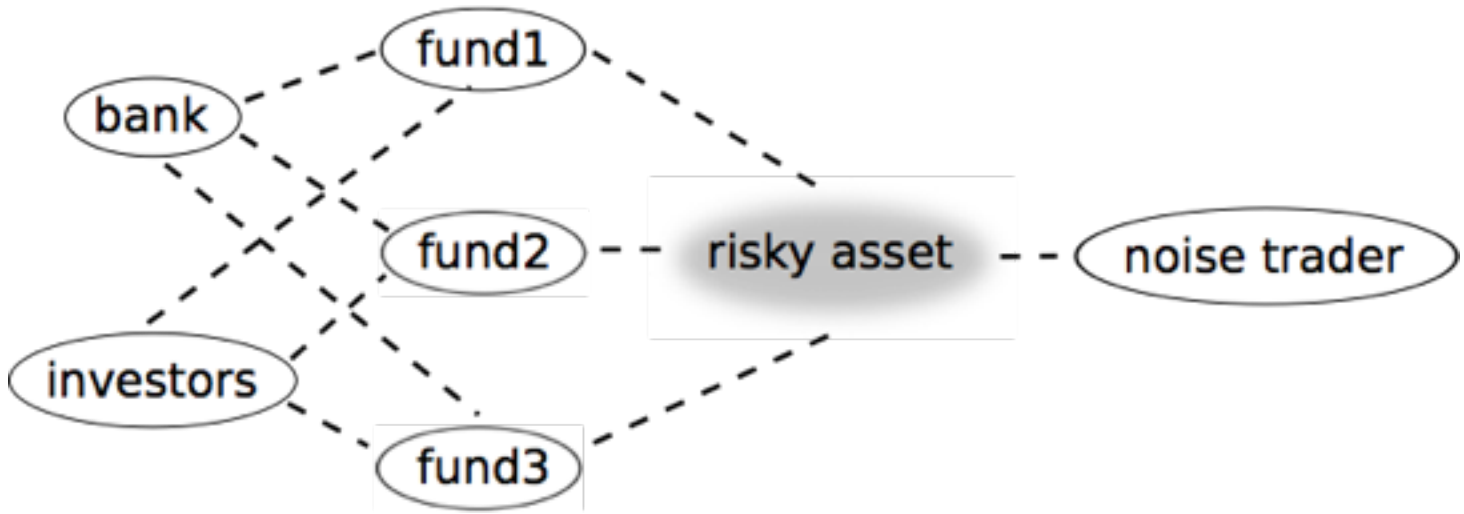
Are there other mechanisms that cause excess volatility and extreme events?

Value investor leverage model

(Thurner, Farmer, Geanakoplos, Quantitative Finance 2011)
(Poledna, Thurner, Farmer, Geanakoplos, J. Banking Finance 2014)

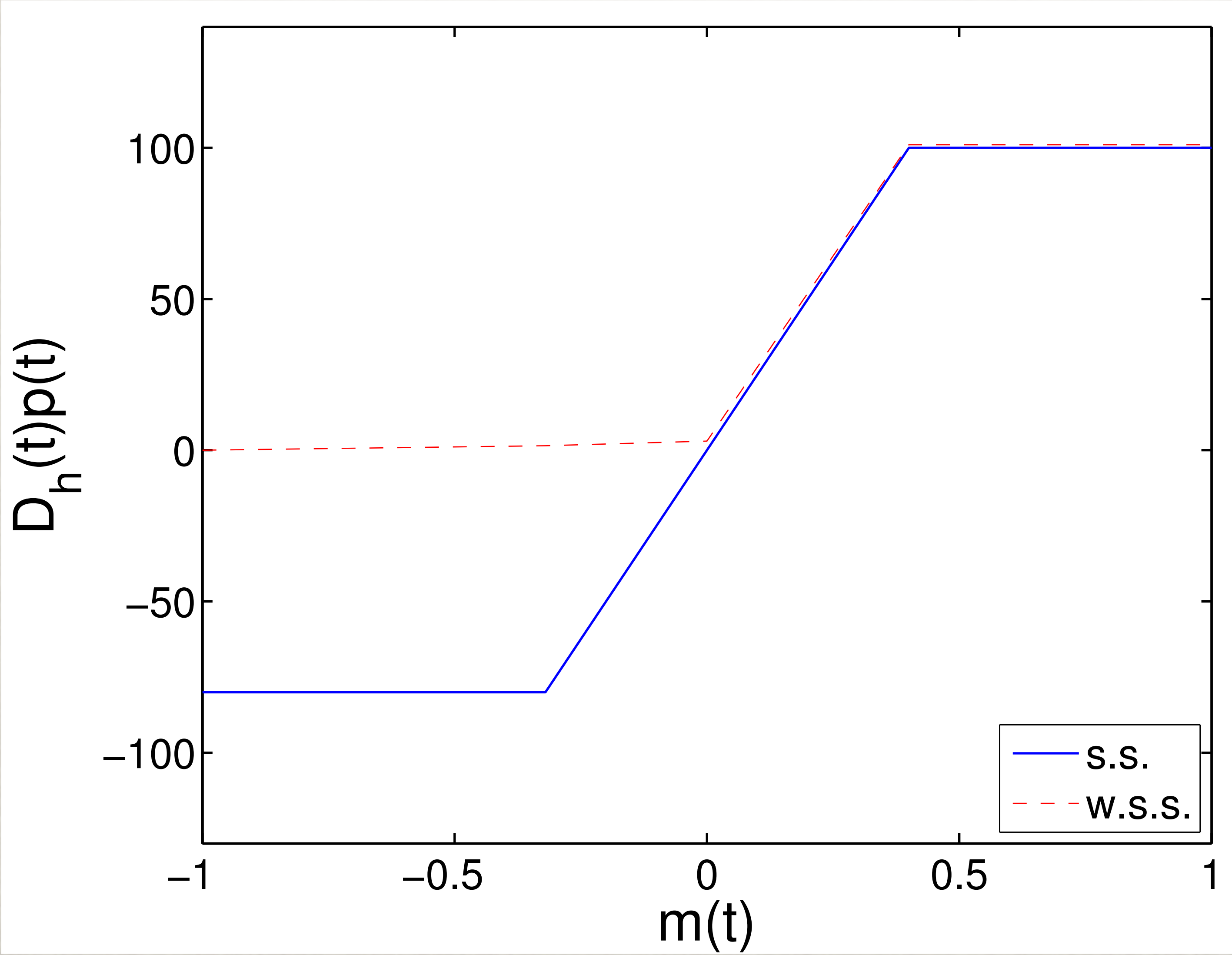
- **funds** (value investors)
- **noise traders** reverting to a fundamental value
- **investors** choosing between fund and cash; base decisions on trailing performance of funds
- **bank** lending to funds
  Note **leverage** is ratio of asset value to equity:
  Leverage > 1 implies debt.
  When prices drop, leverage increases

Model of leverage cycles driven by leveraged value investors



Thurner, Farmer and Geanakoplos (2010)

Value investor's demand



Key fact

For passive investor:

- When prices drop leverage goes up
- When prices rise leverage goes down

Reason:

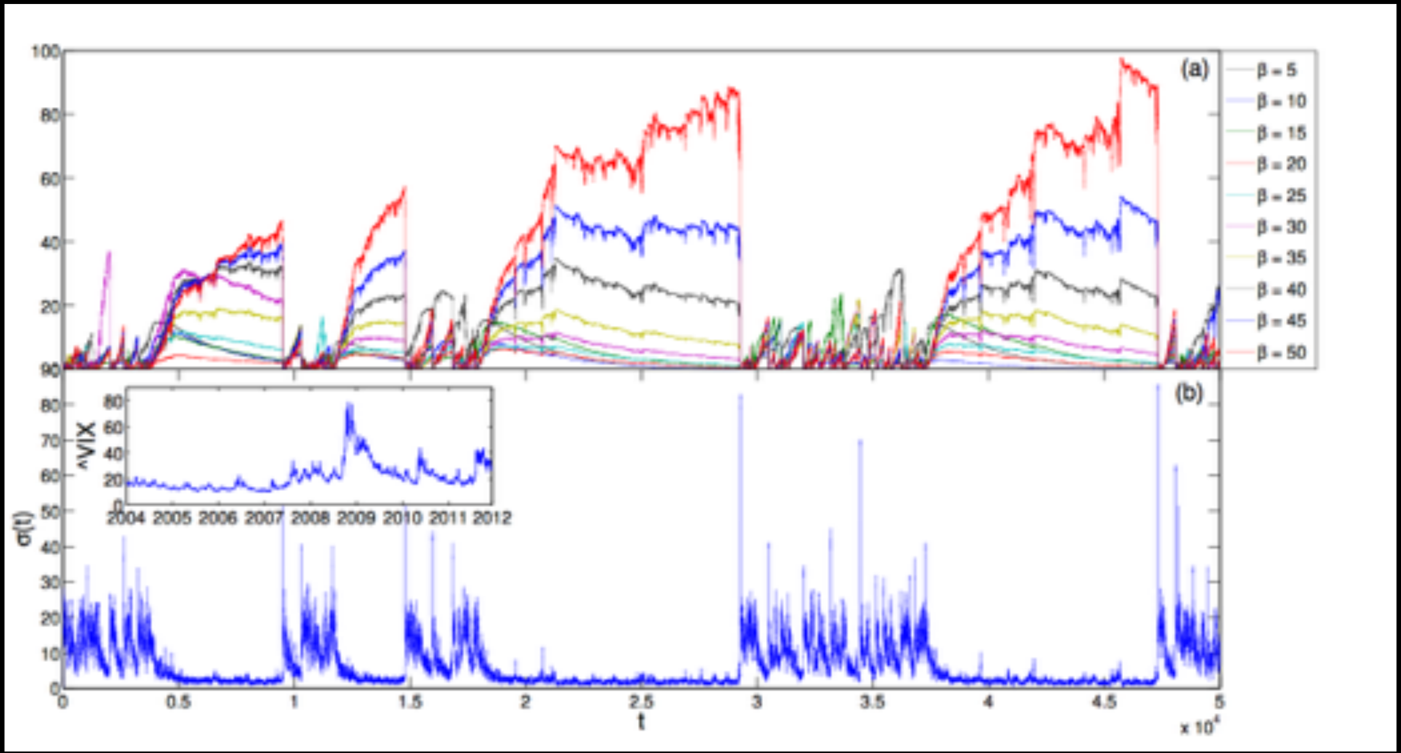
Leverage = Risky assets/(Assets - liabilities)

When assets decrease in value, denominator is smaller, so affected more than numerator

Leveraged hedge fund ABM

Fund wealth

Volatility



- ABM model of leveraged value funds with fundamentalist noise trader
- Investors allocate to funds or cash based on trailing returns (yield chasing)
- Bank lends to funds, bank can make margin calls
- Endogenous build-up in leverage, statistically realistic crashes, volatility (VIX)
- Evolutionary pressure favours more aggressive funds (in the short run)

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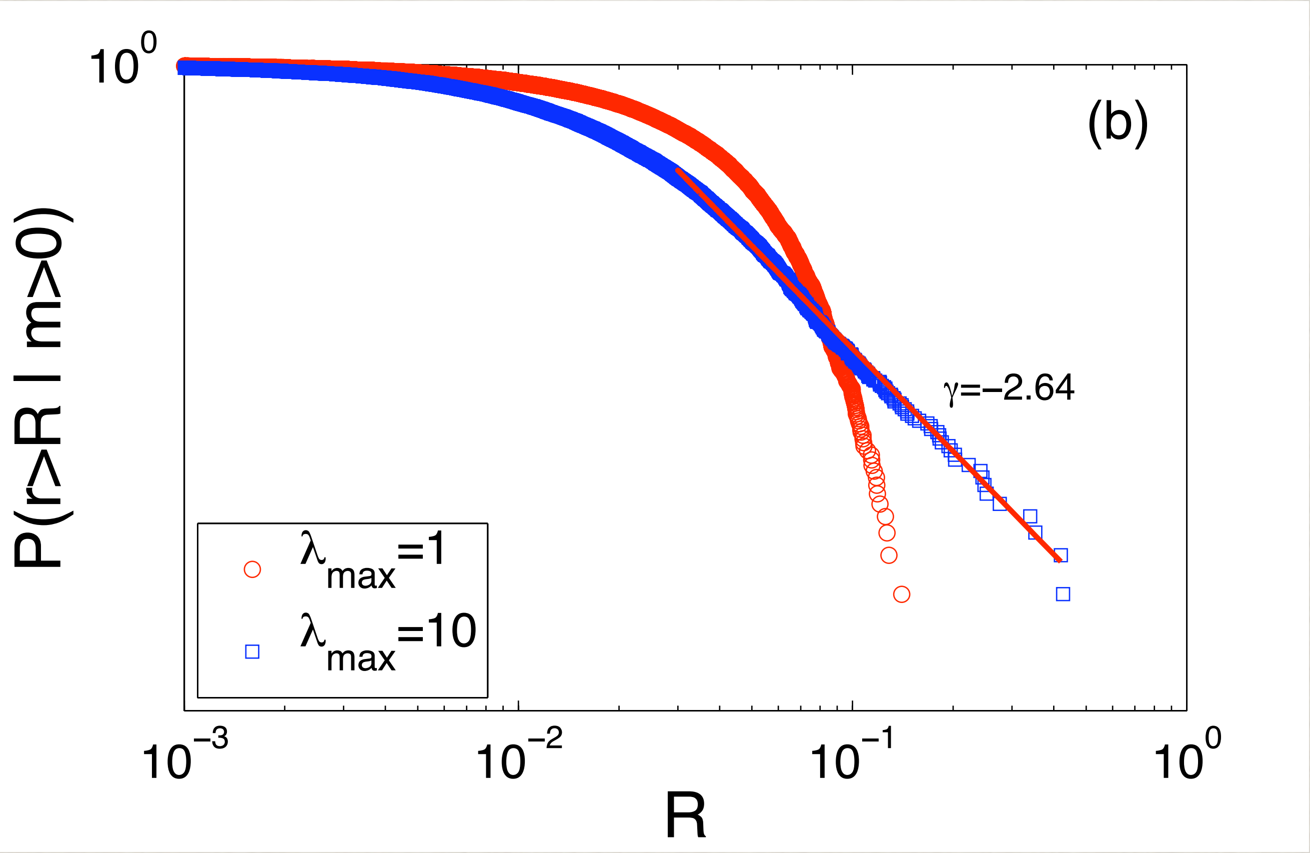
Sources: Thurner, Farmer, Geanakoplos, Quantitative Finance 2010
Poledna, Thurner, Farmer, Geanakoplos, J. Banking Finance 2014

WHY?

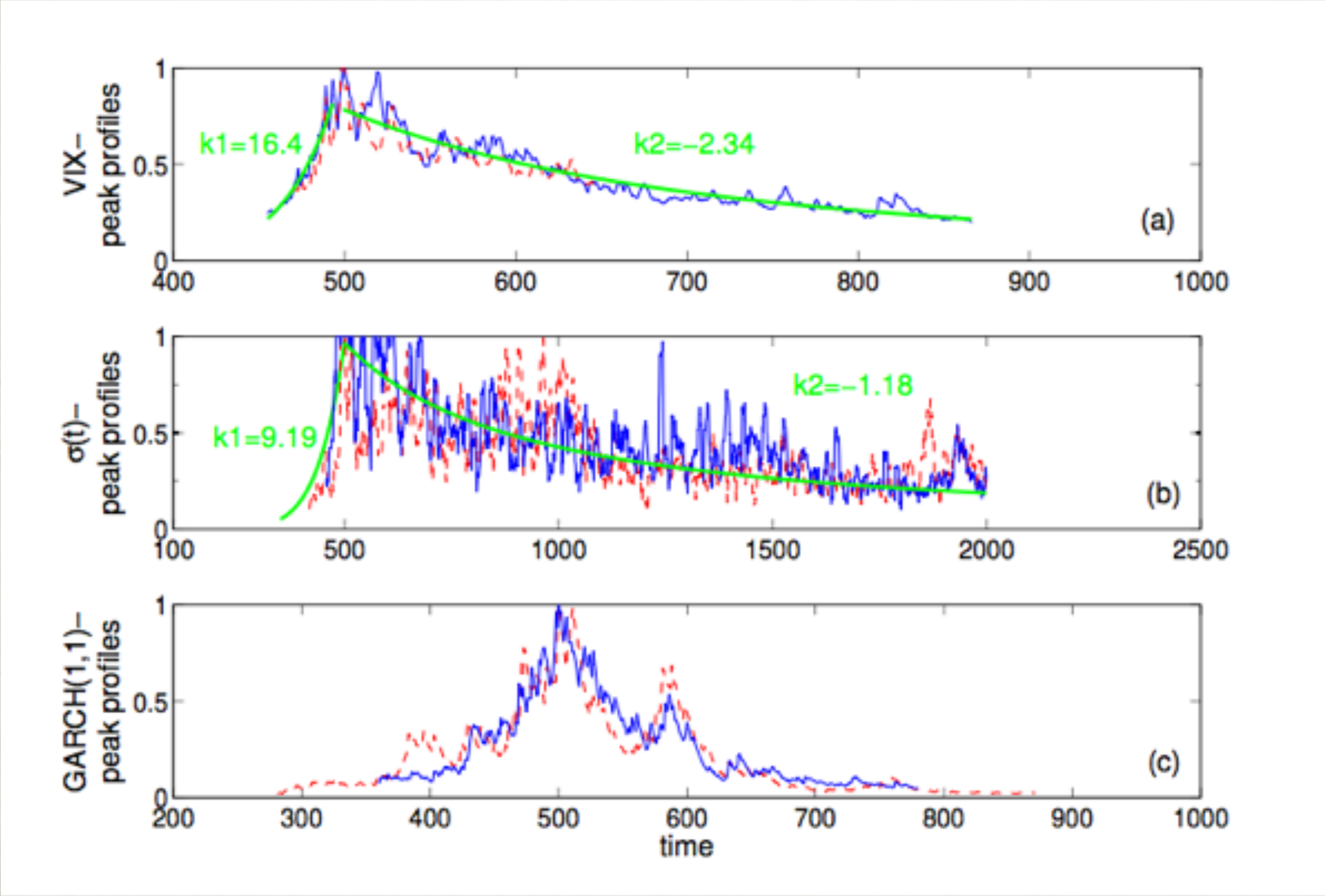
- Value investors are normally stabilizing, buying into falling markets.
- However, when fully leveraged, if price randomly drops, due to risk control by banks, value investors are forced to sell into a falling market.
- This amplifies rather than damps fluctuations.

Leverage causes power law tail for stock returns

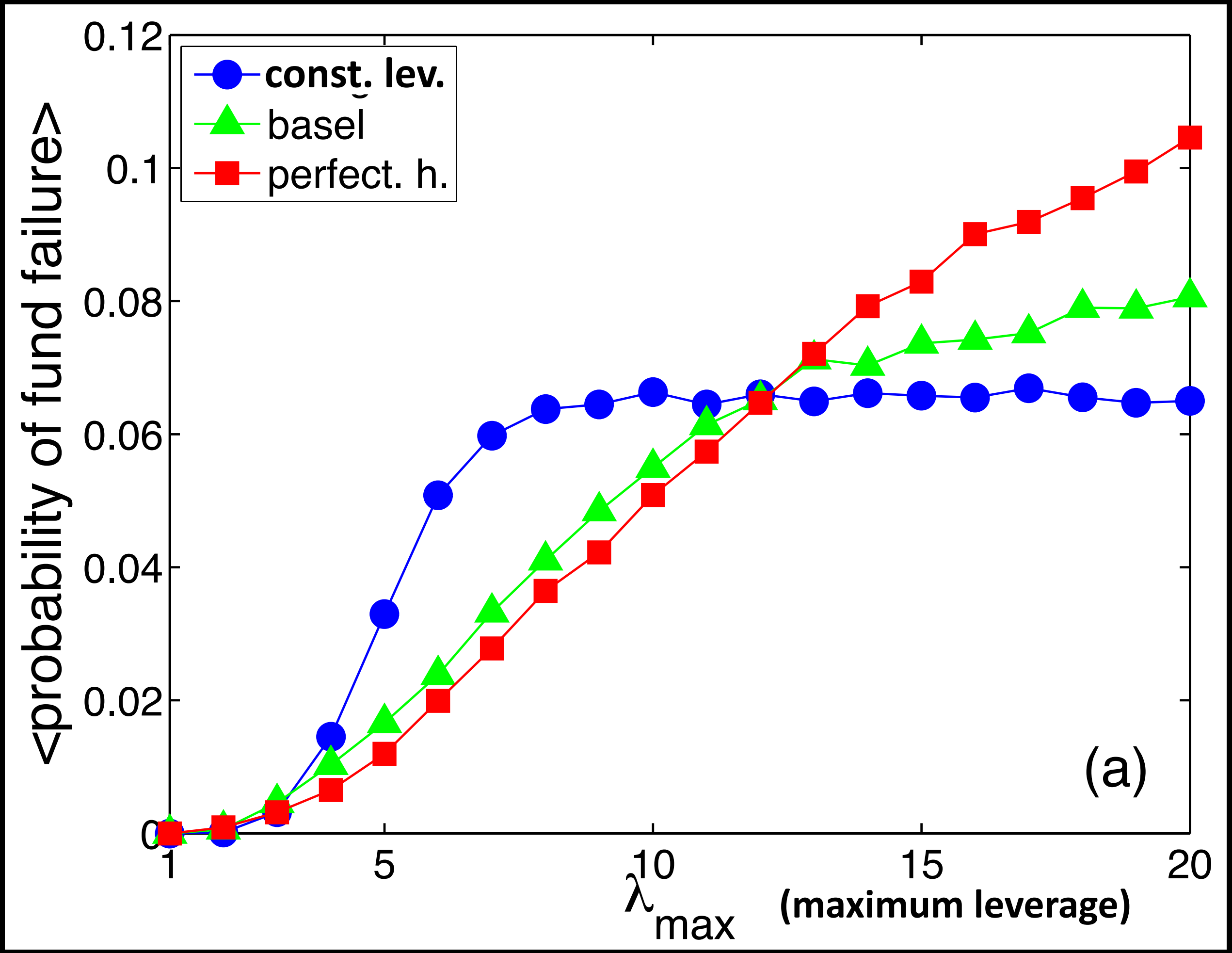


$$P(r > R) \sim R^{-\gamma}$$

ABM reproduces time profile of volatility peaks



Defaults under diverse regulatory regimes



Conclusions

- Basel-style risk control generates chaotic endogenous dynamics and price crashes when leverage + size of banking sector is high.
- Can be understood with a very simple ABM, which can be calibrated to real data.
- Improved risk control policy:
  - more countercyclical than Basel, but not fully countercyclical; depends on size of banking sector
  - allows slower adjustment speed

Market ecology

(Farmer, 2002; Farmer and Skouras 2013)

Friedman paradox

Market efficiency requires arbitrageurs but arbitrageurs require inefficient markets.

- See also Grossman and Stiglitz
- Markets necessarily deviate from efficiency
- It is difficult but not impossible to make consistent profits (e.g. Renaissance, Prediction Company, …)
- Markets are (informationally) efficient at first order but necessarily inefficient at second order

Market ecology hypothesis

- Agents follow specialized strategies that exploit niches, corresponding to inefficiencies generated by activity of other agents
  - cost/benefit => increasing returns to specialization
- Profit relationships define a market food web that specifies who profits from whom
- The market food web evolves with time
- Evolution of new strategies unbalance web
- Imbalances in market food web drive crises

Practical use?

- Stress testing:
  - 1.0: Shock balance sheets of individual banks
  - 2.0: Shock banks and assets and monitor failures as they propagate through network
  - 3.0: Simulate ecology of agents using models calibrated against historical transactions with counterparty identifiers

How is science going to help solving the world's most pressing problems?

Is it possible to make a quantitative ABM that can be used as a time series model?
(and therefore can compete with DSGE)

Agent-based model of housing market

- Goal: conditional forecasts and policy analysis
- Simulation at level of individual households
- Exogenous variables: demographics, interest rates, lending policy, housing supply.
- Predicted variables: prices, inventory, default
- 16 Data sets: Census, mortgages (Core Logic),tax returns (IRS), real estate records (MLA), ...
- Current goal: Model Washington DC metro area
- Future goal: All metro areas in US

Housing model project

- Senior collaborators: Rob Axtell, John Geanakoplos, Peter Howitt
- Junior collaborators: Ernesto Carella, Ben Conlee, Jon Goldstein, Matthew Hendrey, Philip Kalikman
- Funded by INET three years ago for $375,000.

Module examples

- Desired expenditure model
  - buyers' desired home price as a function of household income and wealth
- Seller's pricing model
  - seller's offering price as a function of home quality, time on market, and total inventory
- Buyer-seller matching algorithm
  - links buyers and sellers to make transactions
- Household wealth dynamics
  - models consumption and savings
- Loan approval
  - qualifies buyers for loans based on income, wealth; must match issued mortgages

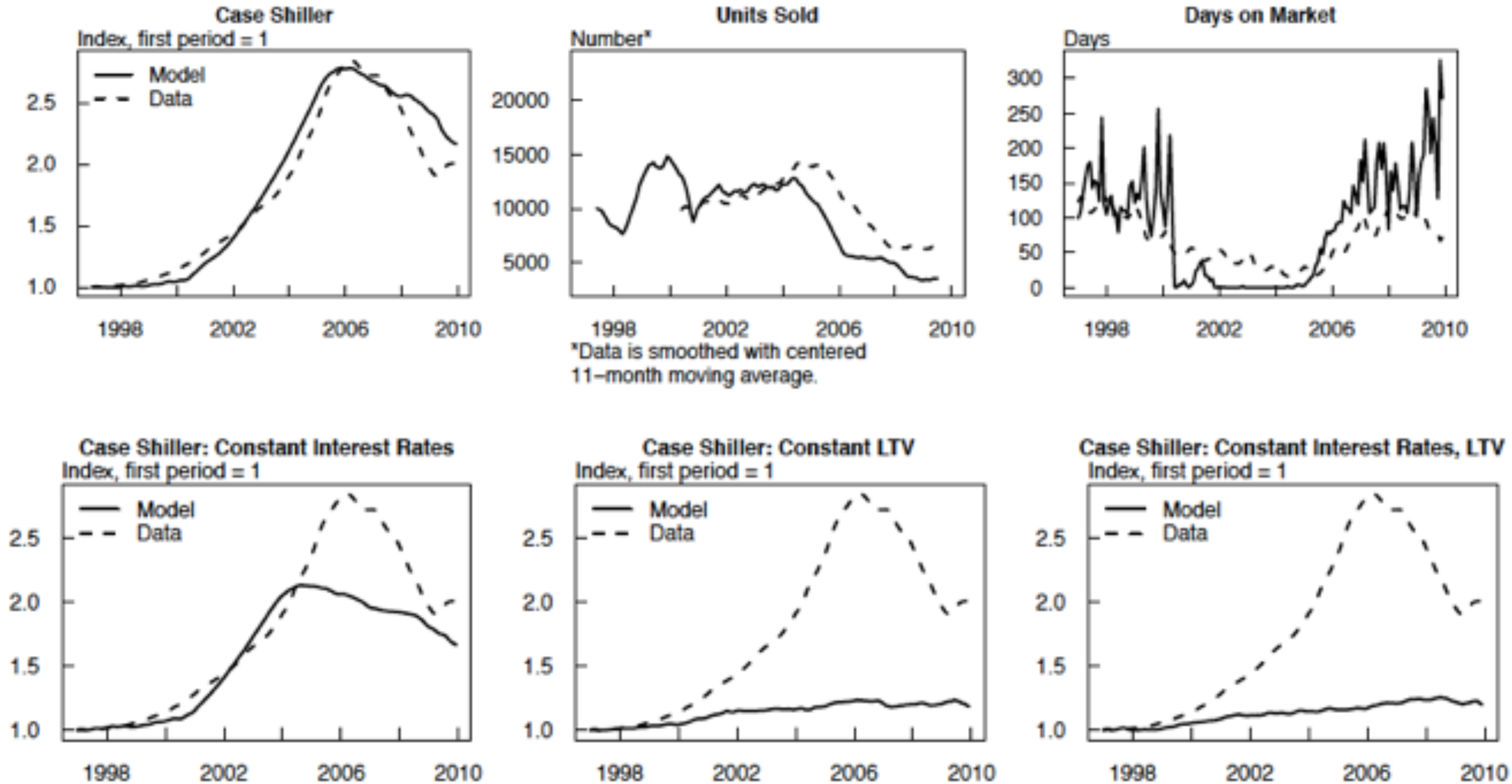
Housing model algorithm

At each time step:

- Input changes to exogenous variables
- Update state of households
  - income, consumption, wealth, foreclosures, ...
- Buyers:
  - Who? Price range? Loan approval, terms?
- Sellers:
  - Who? Offering price? Price updates?
- Match buyers and sellers
  - Compute transactions and prices

Results when we fit parameters to match the target data

Results obtained by hand-fitting parameters

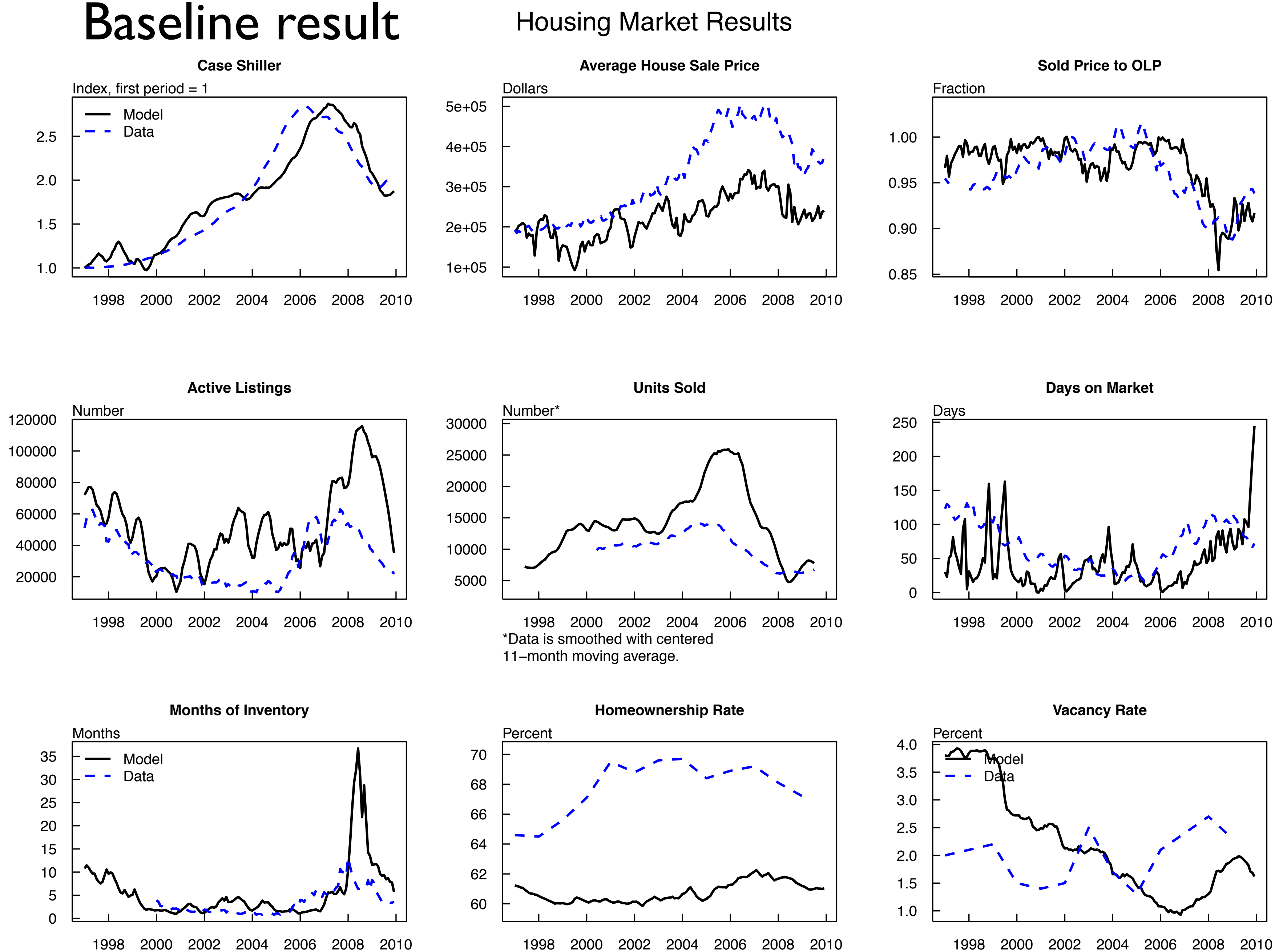


(this is an early slide)

Tentative conclusion: Lending policy is dominant cause of housing bubble in Washington DC.

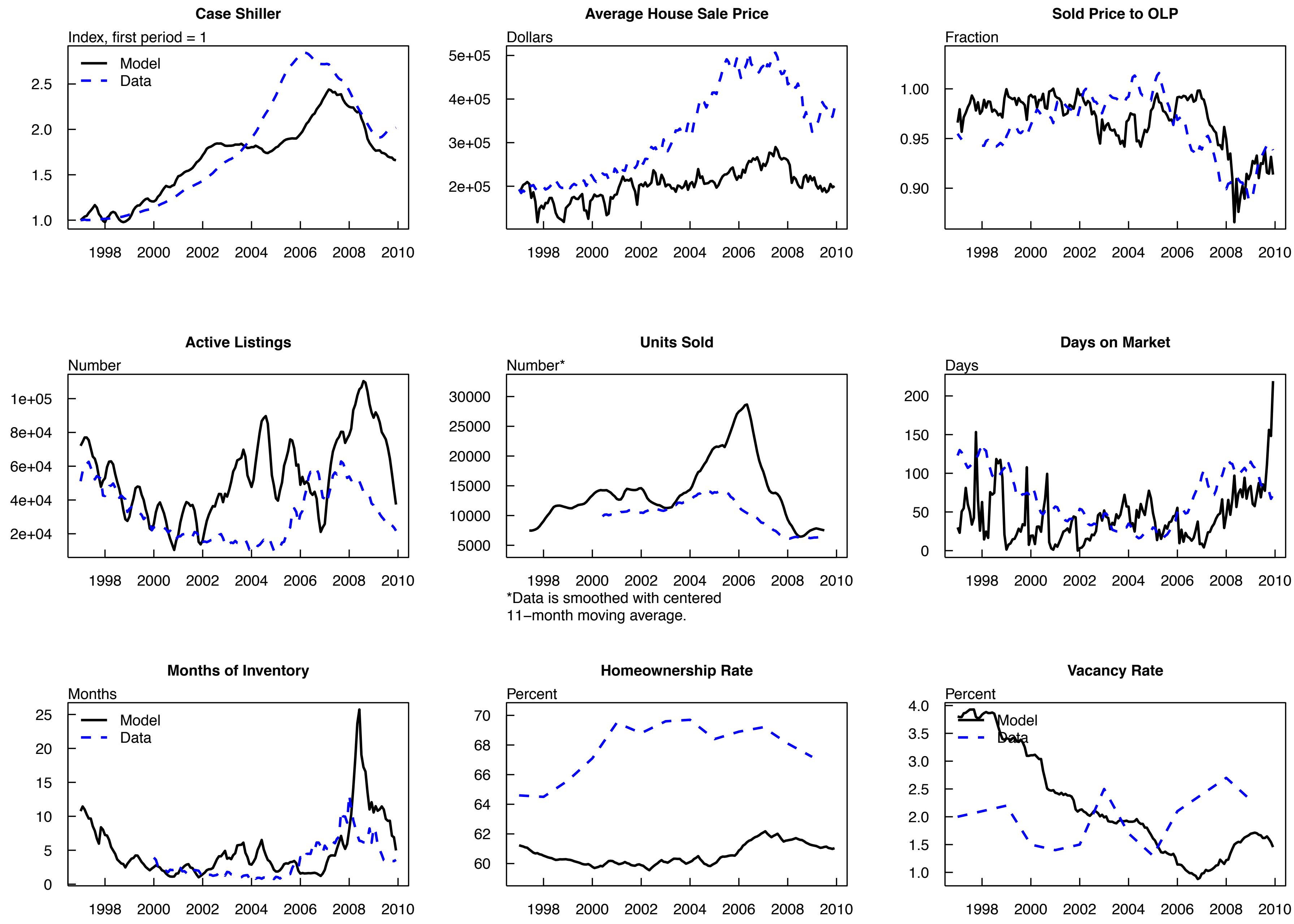
Results when we fit each module separately on data that is not the target data.

Baseline result



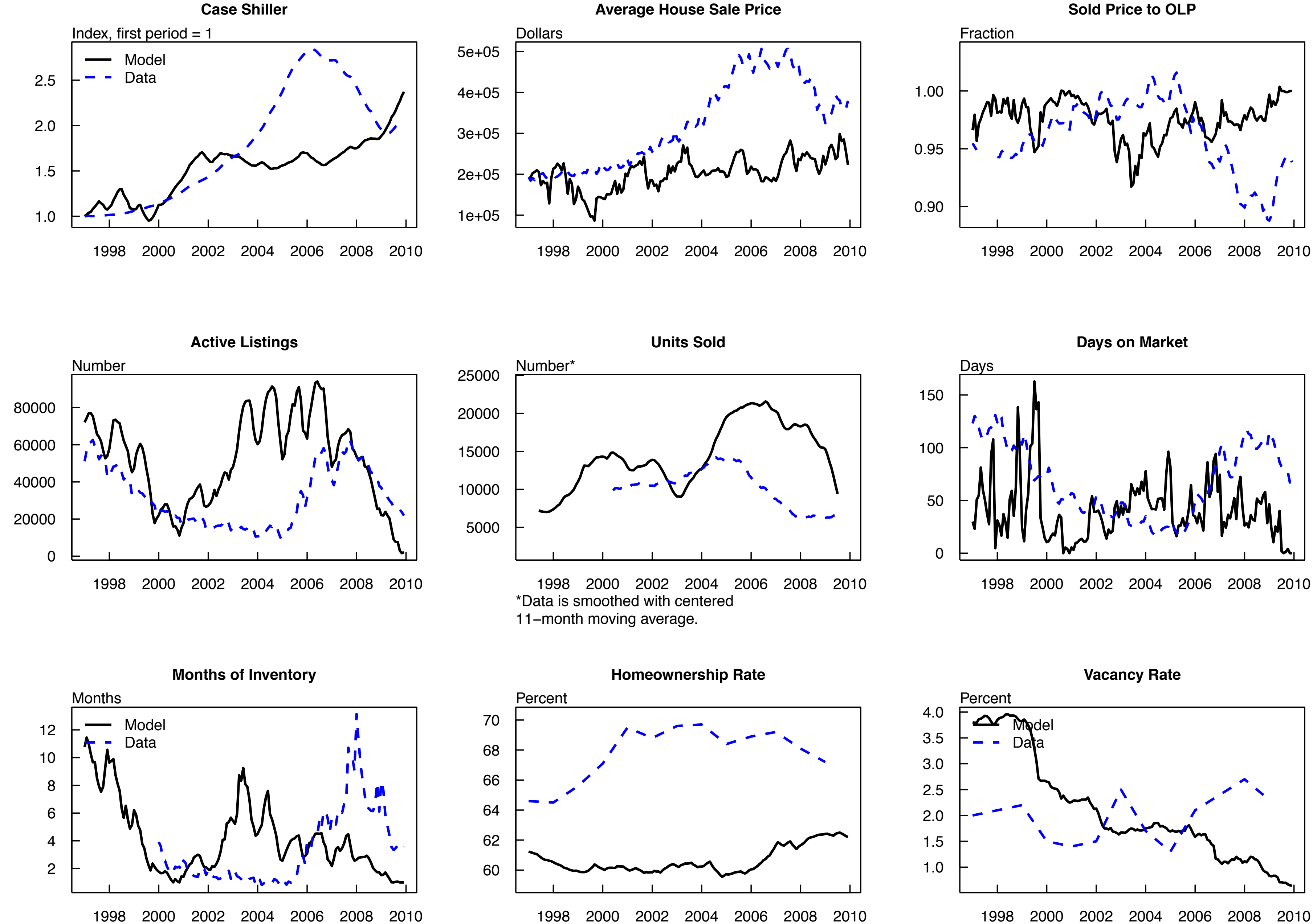
fixed interest rate

Housing Market Results



fixed lending policy

Housing Market Results



Economic agent project
(with David Pugh and Dan Tang)

- Economic agents are special because
  - they have balance sheets
  - interact with markets
  - form expectations
  - make contracts
- Embody with modern software (Scala, Akka, ..)
- Open source project “wiki-economics”.

What are the scientific problems you would like to solve personally, but also what would you hope could be achieved in your lifetime by the community you are part of?

My vision

- Real time tandem simulation of economies of the major countries of the world.
- Inputs directly from internet.
- Coupled to other social models?
- Used by central banks
- Teams focusing on each component, e.g. households, firms, banks, …

My vision

- Would forecast unemployment, economic prosperity, …
  - *would not* forecast stock market, interest rates, …
- Variant would be an integrated assessment model for economy- environment interactions.
- These models would be built out of a library of standard plug and play components.
  - similar to current climate models

Concluding thoughts

- We have lots of work to do to make agent-based models that can compete with or surpass existing alternatives
- Must solve chicken and egg problem
- In economic models of future (e.g. for central banks) ABM will play a prominent role
  - but when?