Economics from a physics point of view

Complex Systems Summer School
June 30, 2015

J. Doyne Farmer

Mathematical Institute and

Institute for New Economic Thinking at the Oxford Martin School

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Institute for
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AT THE OXFORD MARTIN SCHOOL

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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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

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!

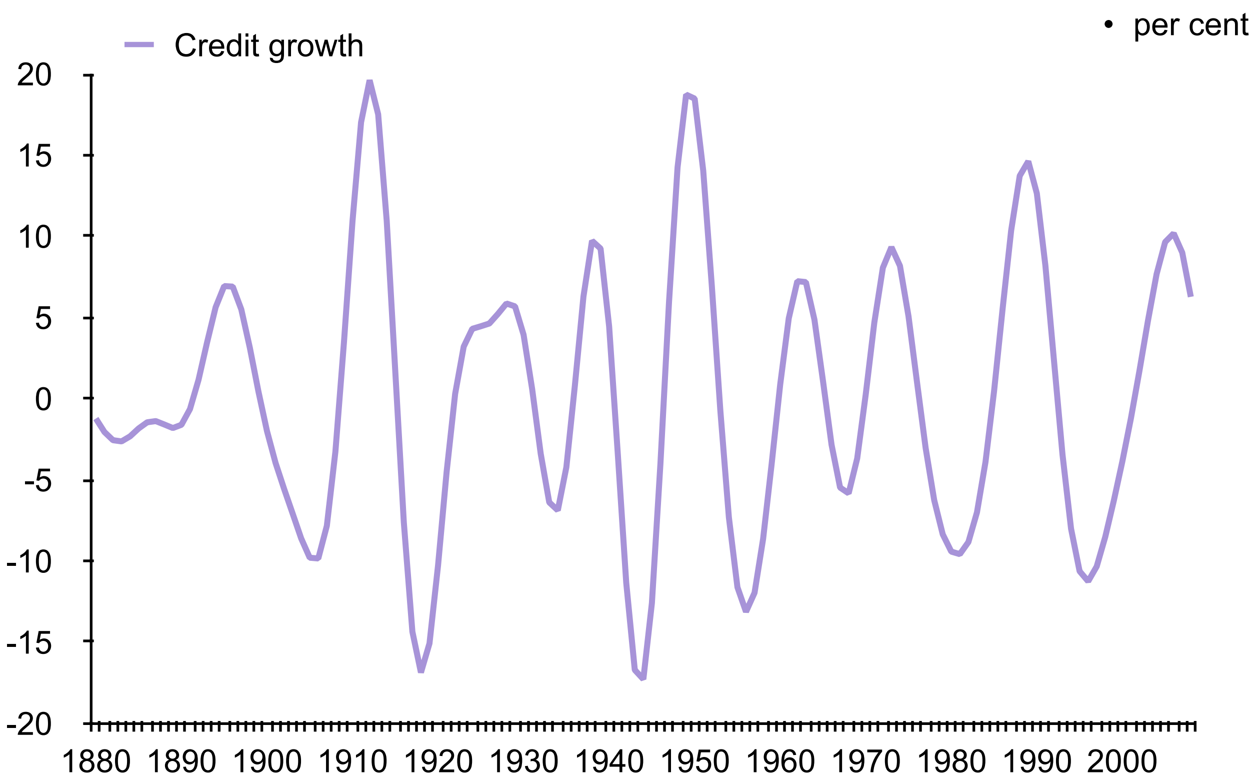
Largest S&P index moves 1946-87

(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?

Credit Cycles



• Source: Bank calculations

History of 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)

Causes of leverage cycles

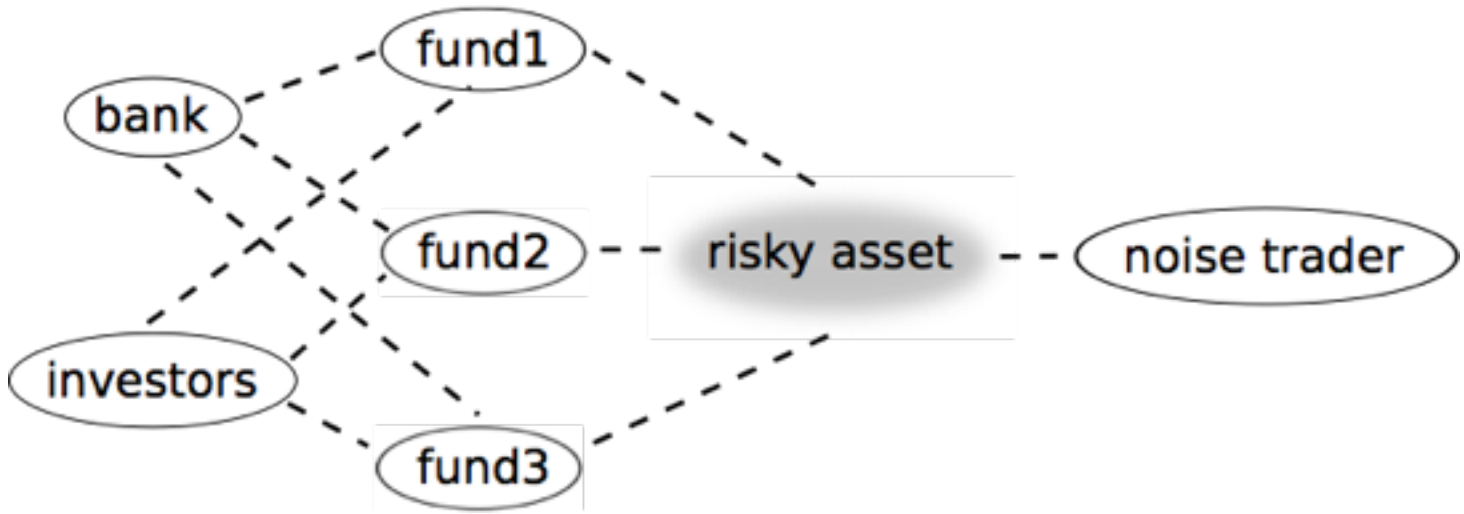
- Minsky: During calm times leverage does up due to competition for returns. With high leverage negative shocks are amplified by leverage, which triggers a crash
- Geanakoplos: Heterogenous investors, optimists use more leverage, bad news is amplified

Value investor leverage model

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

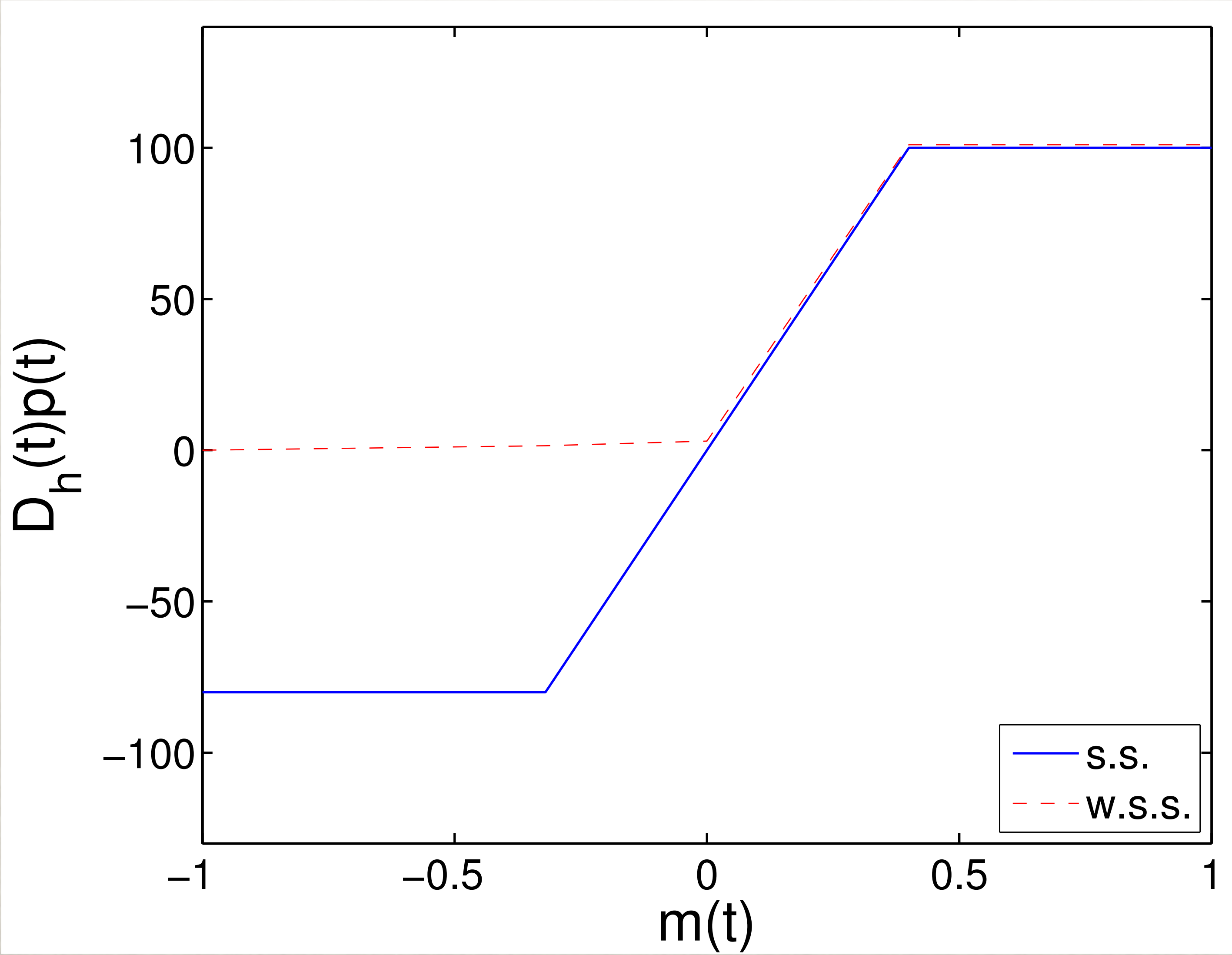
- **funds** (value investors)
- **noise traders** reverting to a fundamental value
- **investors** choosing between fund and cash; base decisions on trailing performance of funds
- **bank** lending to funds
  Note **leverage** is ratio of asset value to equity:
  Leverage > 1 implies debt.
  When prices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

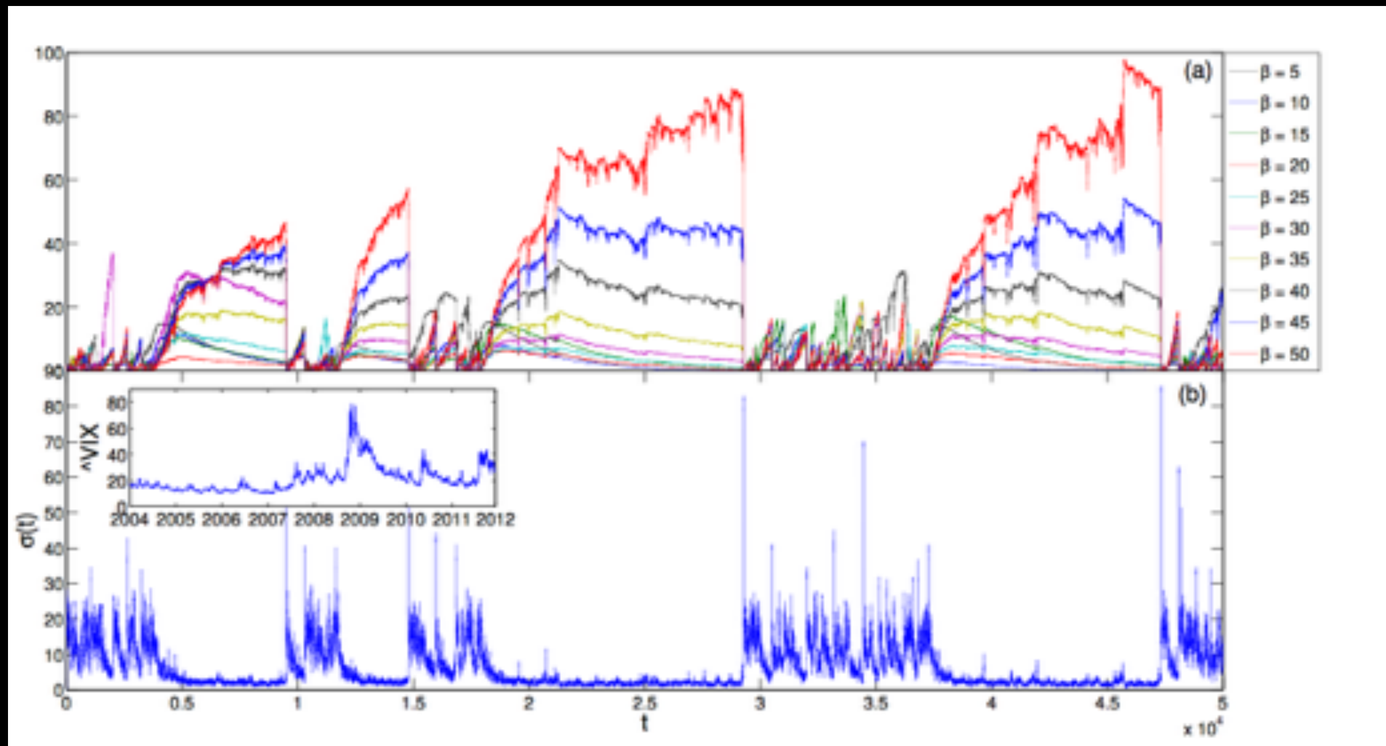
Leverage = Risky assets/(Assets - liabilities)

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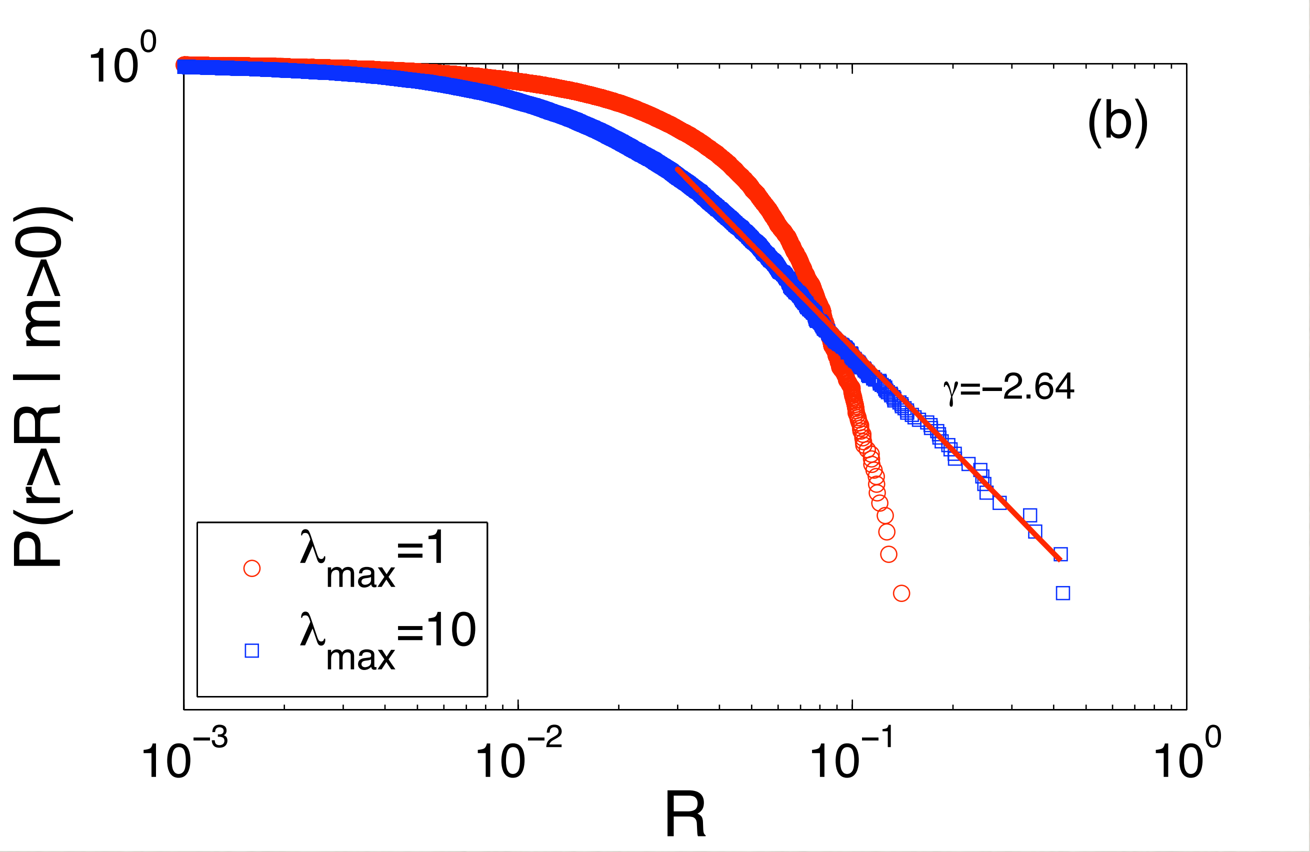
Sources: Thurner, Farmer, Geanakoplos, Quantitative Finance 2010
Poledna, Thurner, Farmer, Geanakoplos, J. Banking Finance 2014

Why?

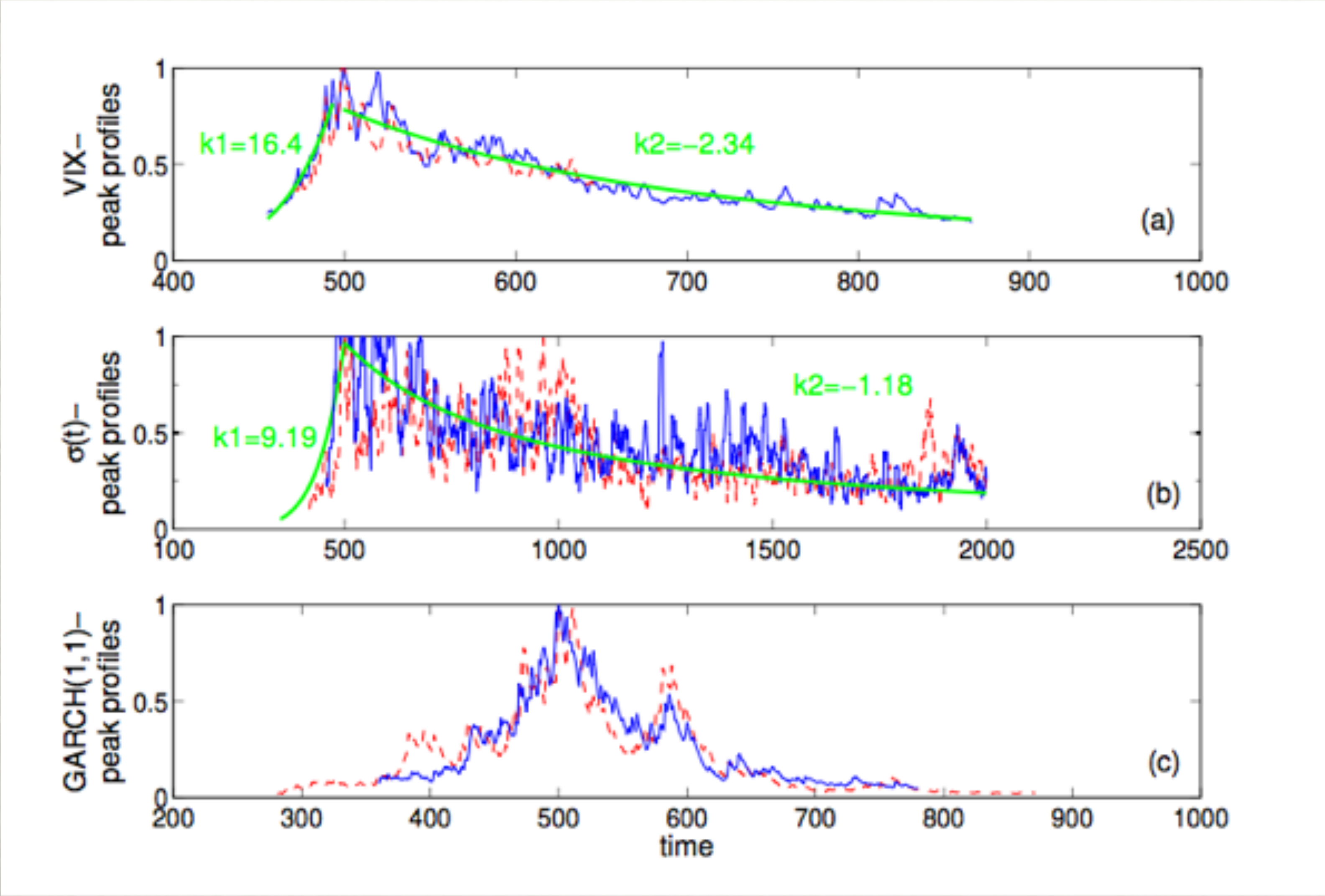
- Value investors are normally stabilizing, buying into falling markets.
- However, when fully leveraged, if price randomly drops, due to risk control by banks, value investors are forced to sell into a falling market.
- This amplifies rather than damps fluctuations.

Leverage causes power law tail for stock returns

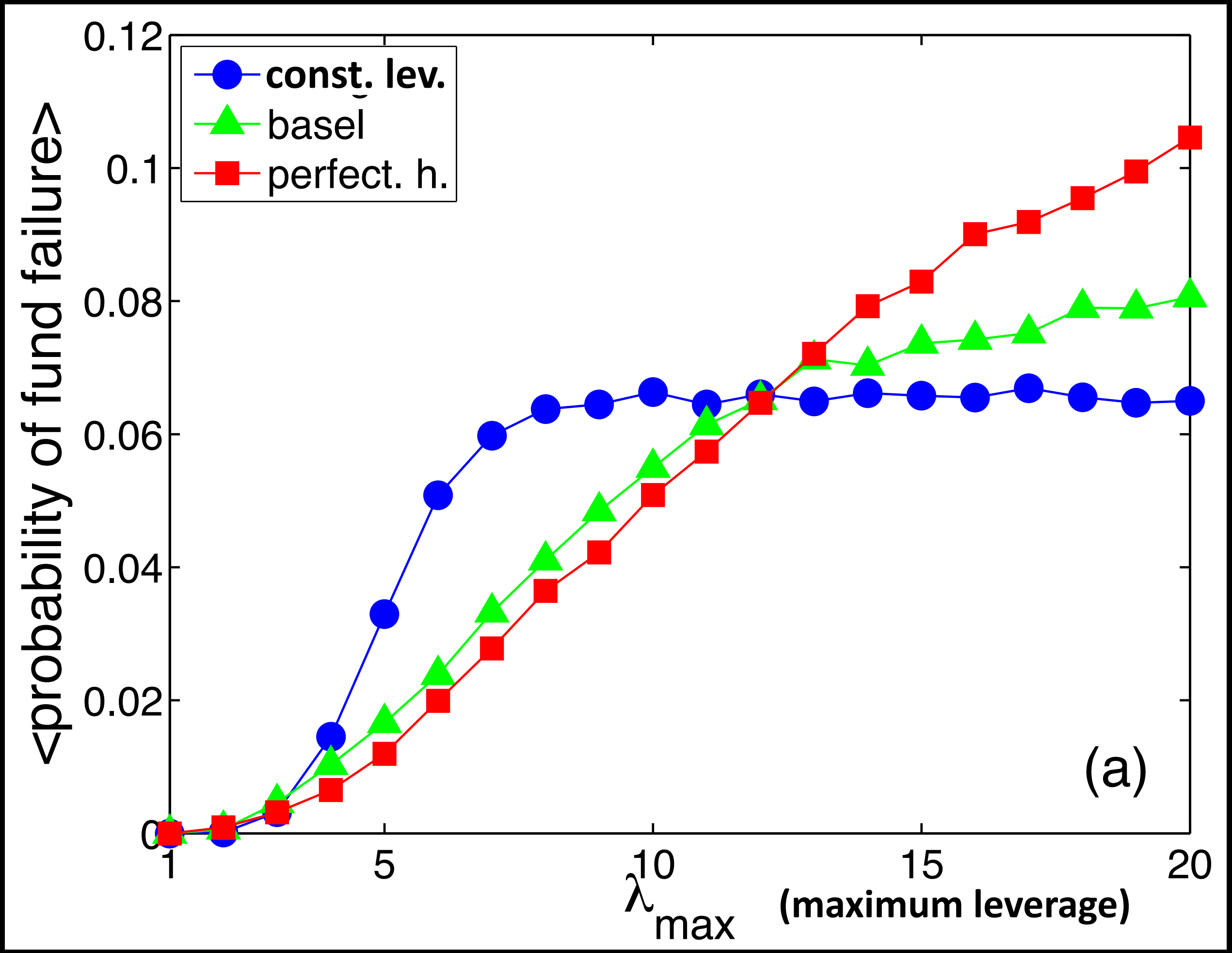


$$P(r > R) \sim R^{-\gamma}$$

ABM REPRODUCES TIME PROFILE OF VOLATILITY PEAKS



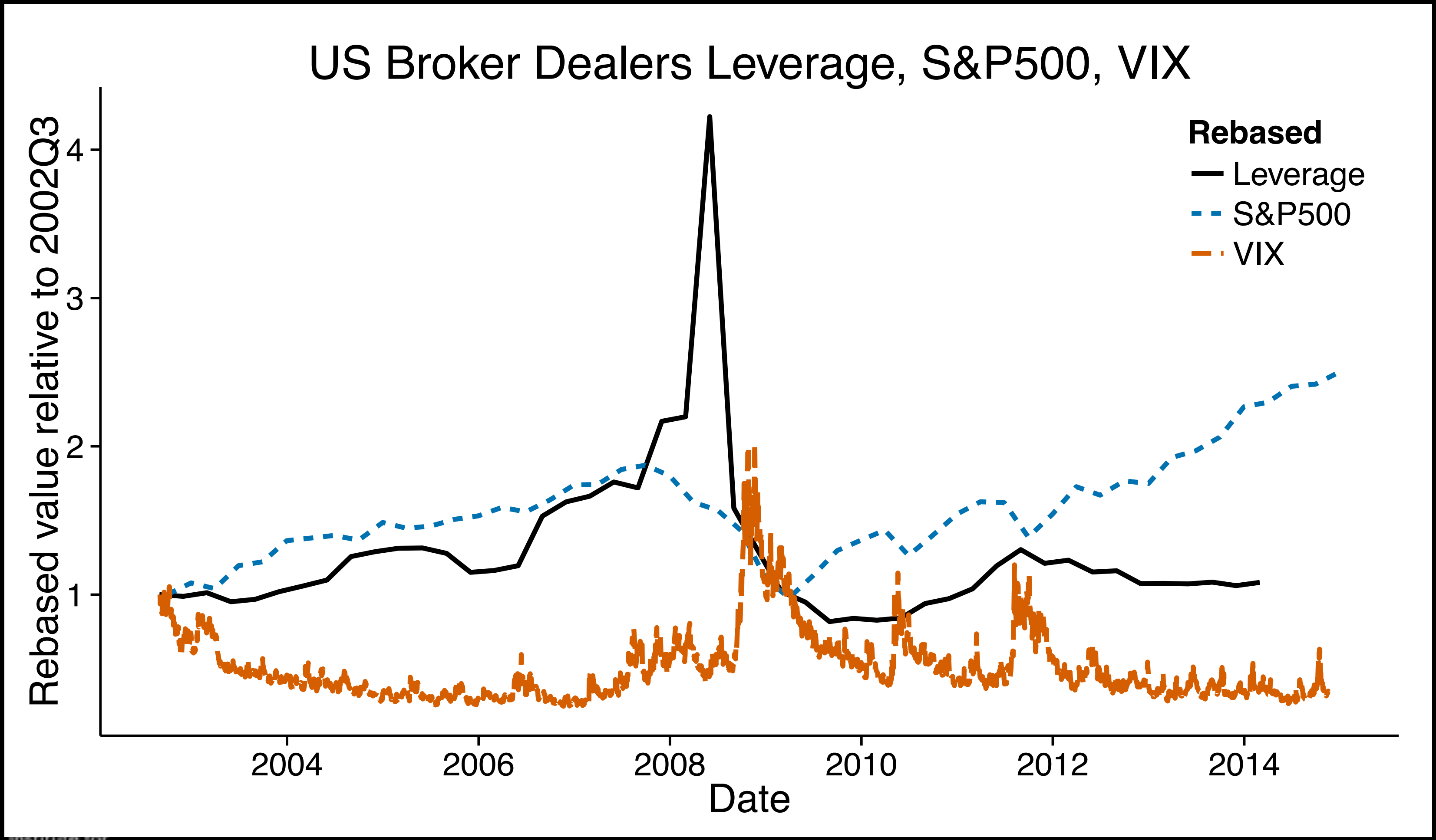
Defaults under diverse regulatory regimes



Model for banks

How do banks differ from leveraged funds?

- Funds are destabilizing when fully leveraged
- Leverage targets (banks) are inherently destabilizing all the time:
  - 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



US Broker Dealers Leverage, S&P500, VIX
Rebased value relative to 2002Q3
4
3
2
1
2004
2006
2008
2010
2012
2014
Date
Rebased
Leverage
S&P500
VIX

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

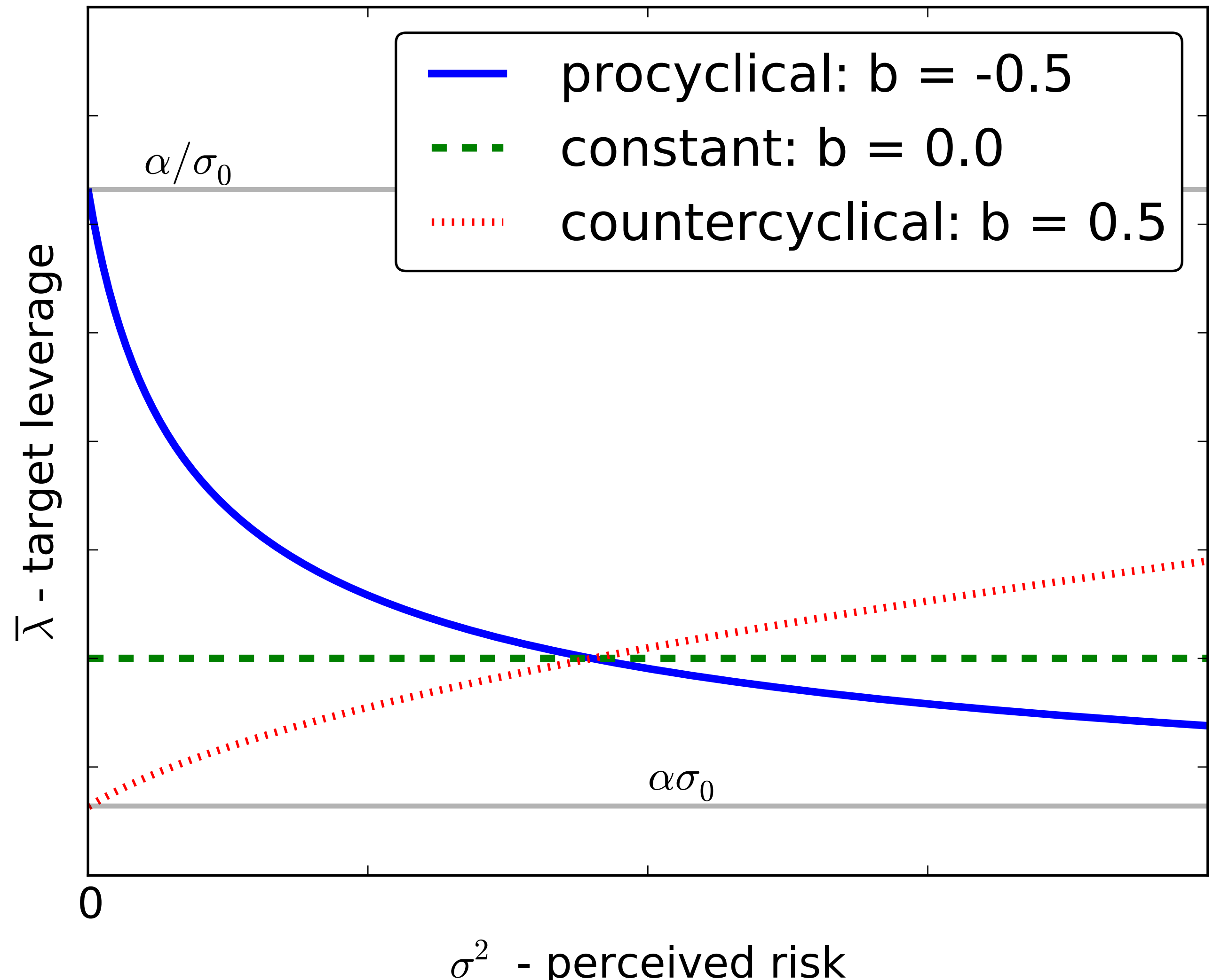
$$\lambda' = \frac{A(t)}{A(t)-\mathcal{L}(t)} \qquad \bar{\lambda} = \frac{A(t)+\Delta\mathcal{B}}{A(t)-\mathcal{L}(t)}$$

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

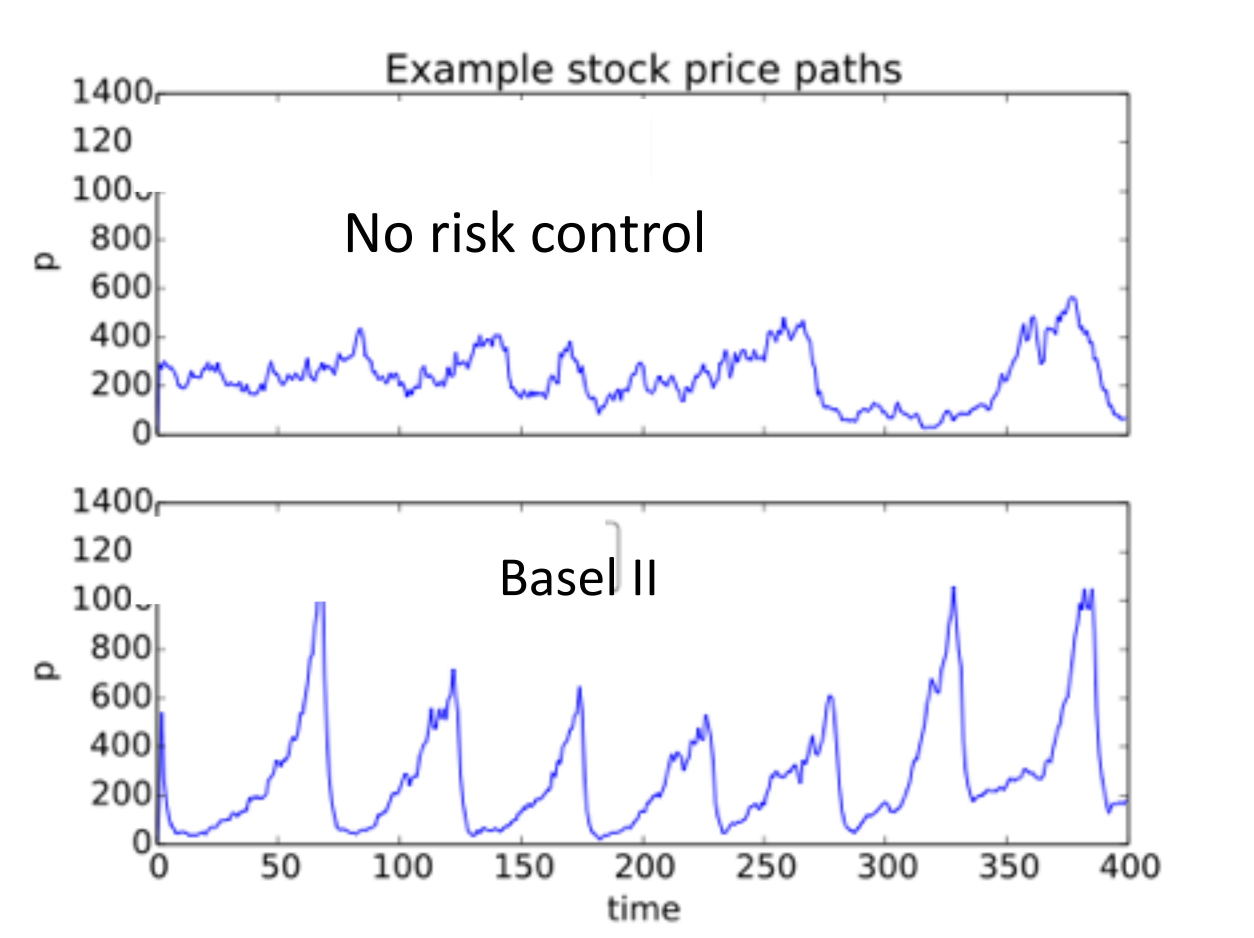
Commercial banks vs. investment banks

- 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



Complicated agent based model with multiple banks and funds, real economy



Simplify to get essence

(Dynamics of the leverage cycle, Aymanns and Farmer, 2014)

- 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

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

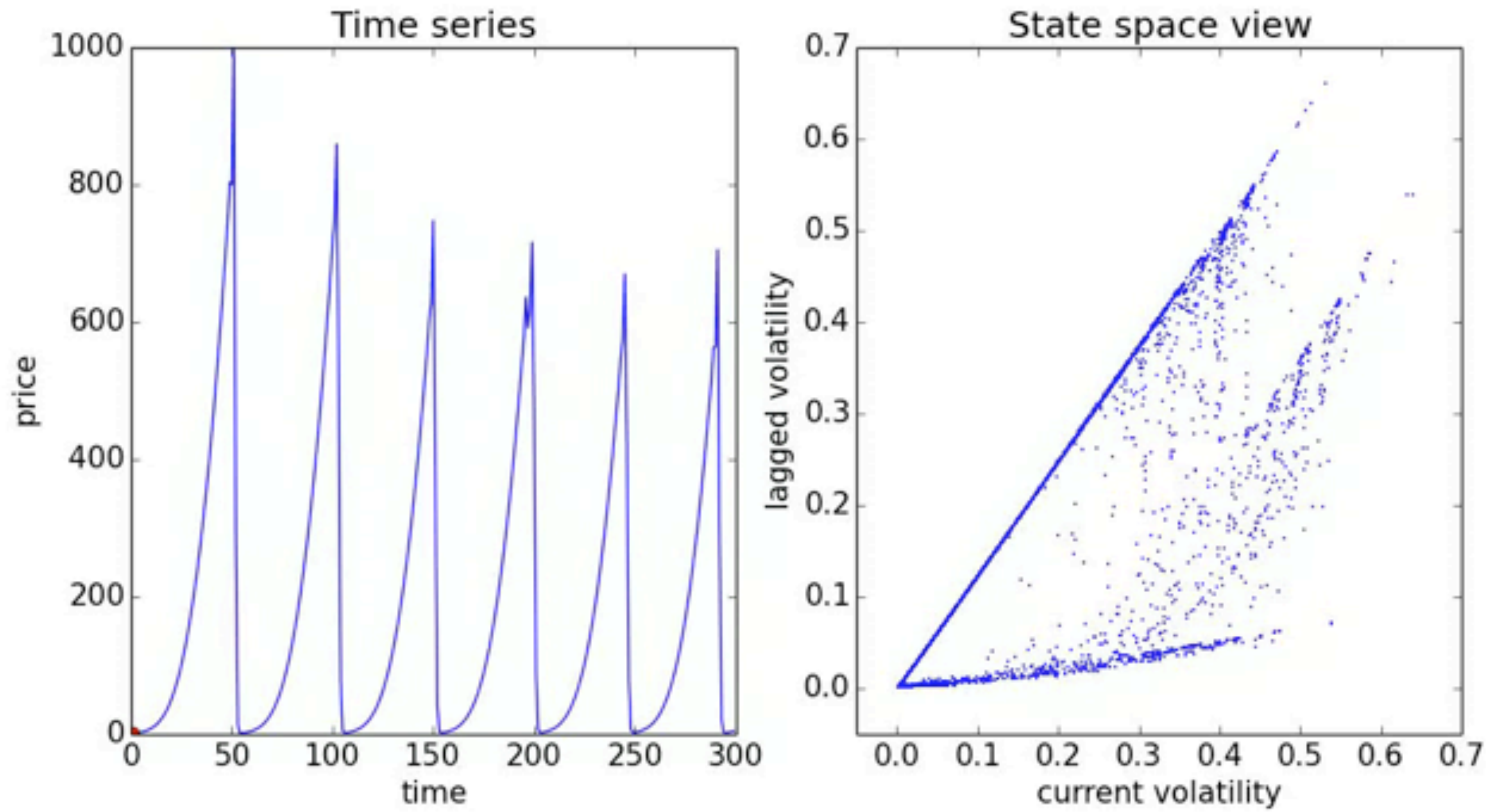
$$\sigma^2(t+1) = (1-\delta)\sigma^2(t) + \delta\left(\log\left(\frac{p(t)}{p(t-1)}\right)\right)^2,$$

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

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
0
200
400
600
800
1000
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

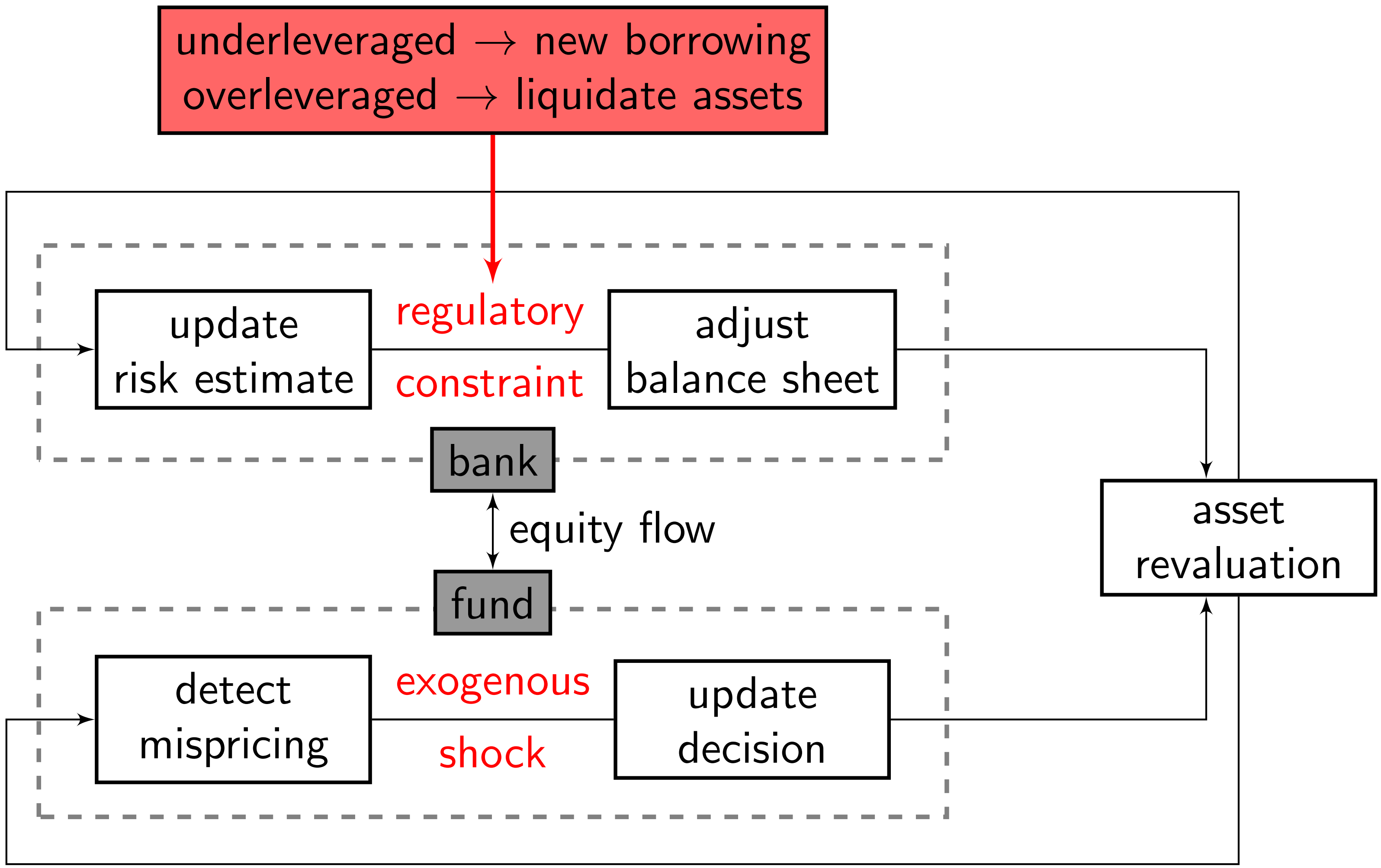
More realistic model

(Aymanns, Caccioli, Farmer, Tan, 2015)

- One bank, one asset
- Key additional ingredient: "Noise trader" (unleveraged fundamentalist) that trades with bank
- Trading of fundamentalist has random term that follows an exogenous GARCH process, which has clustered volatility

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


underleveraged → new borrowing
overleveraged → liquidate assets
update
risk estimate
regulatory
constraint
adjust
balance sheet
bank
equity flow
fund
asset
revaluation
detect
mispricing
exogenous
shock
update
decision

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

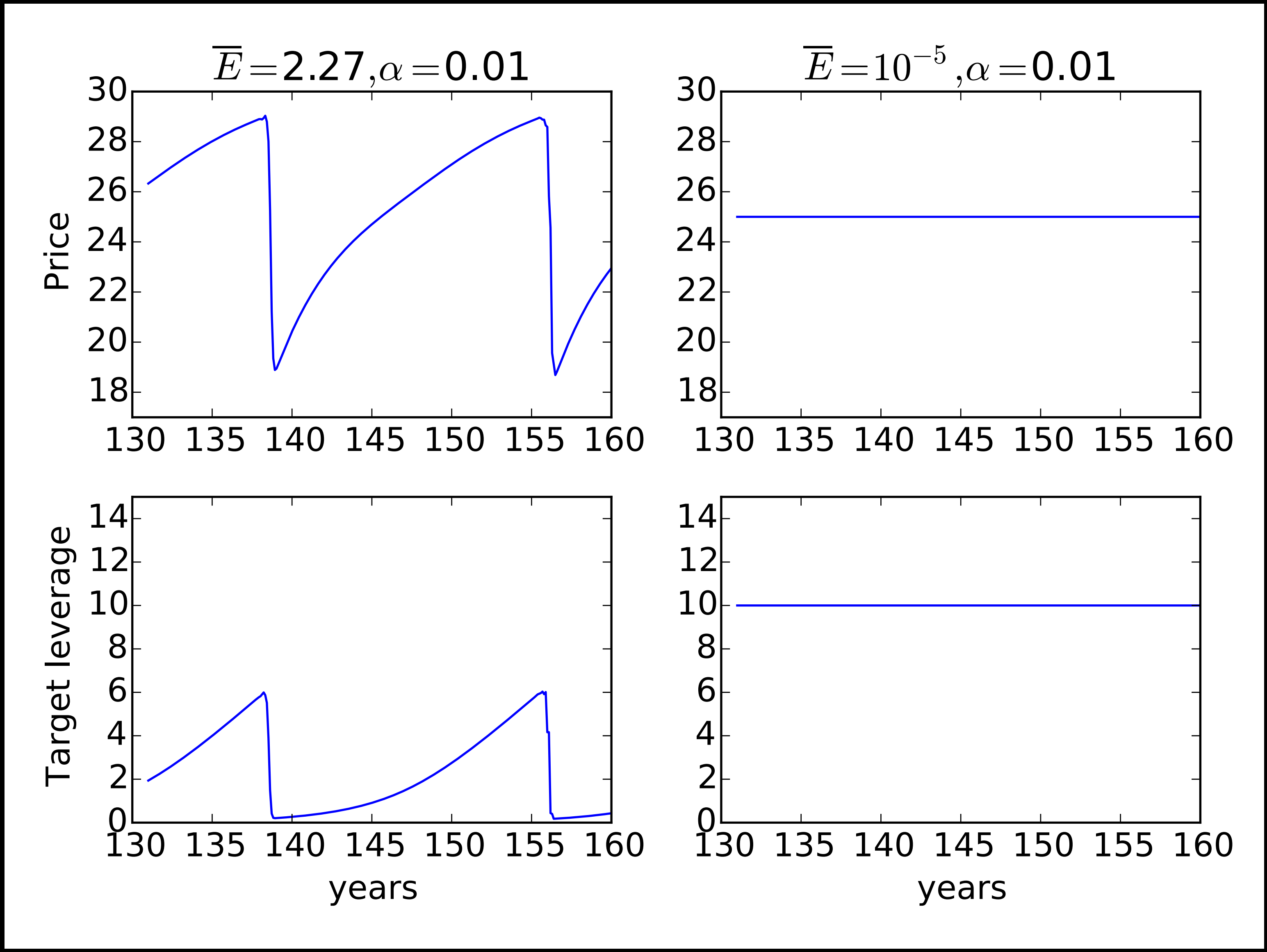
(5) Liabilities: $L(t+\tau) = L(t) + \Delta B(t),$

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

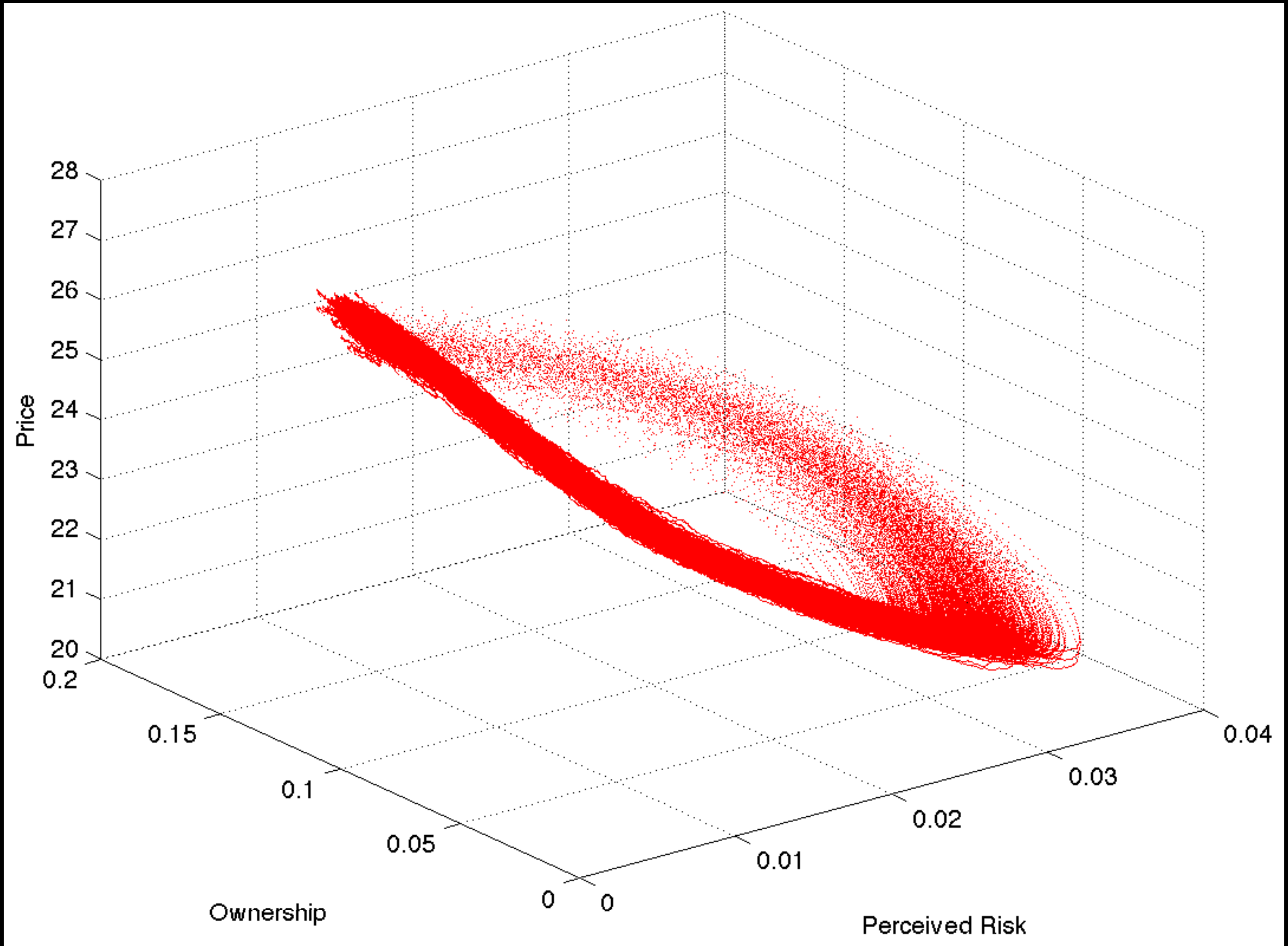
$$\Delta B(t) = \tau\theta(\overline{\lambda}(t)(A(t) - L(t)) - A(t))$$

useful definitions

$$
\begin{aligned}
A(t) &= p(t)n(t)/w_B, \\
\overline{\lambda}(t) &= \alpha(\sigma^2(t) + \sigma_0^2)^b, \\
\Delta B(t) &= \tau\theta(\overline{\lambda}(t)(A(t) - L(t)) - A(t)), \\
\Delta E(t) &= \tau\eta(\overline{E} - (A(t) - L(t))), \\
c(t) &= (1 - w_B)n(t)p(t)/w_B + \Delta E(t), \\
c_F(t) &= (1 - w_F(t))(1 - n(t))p(t)/w_F(t) - \Delta E(t)
\end{aligned}
$$



$\overline{E}=2.27, \alpha=0.01$
$\overline{E}=10^{-5}, \alpha=0.01$
Price
Target leverage
years
years



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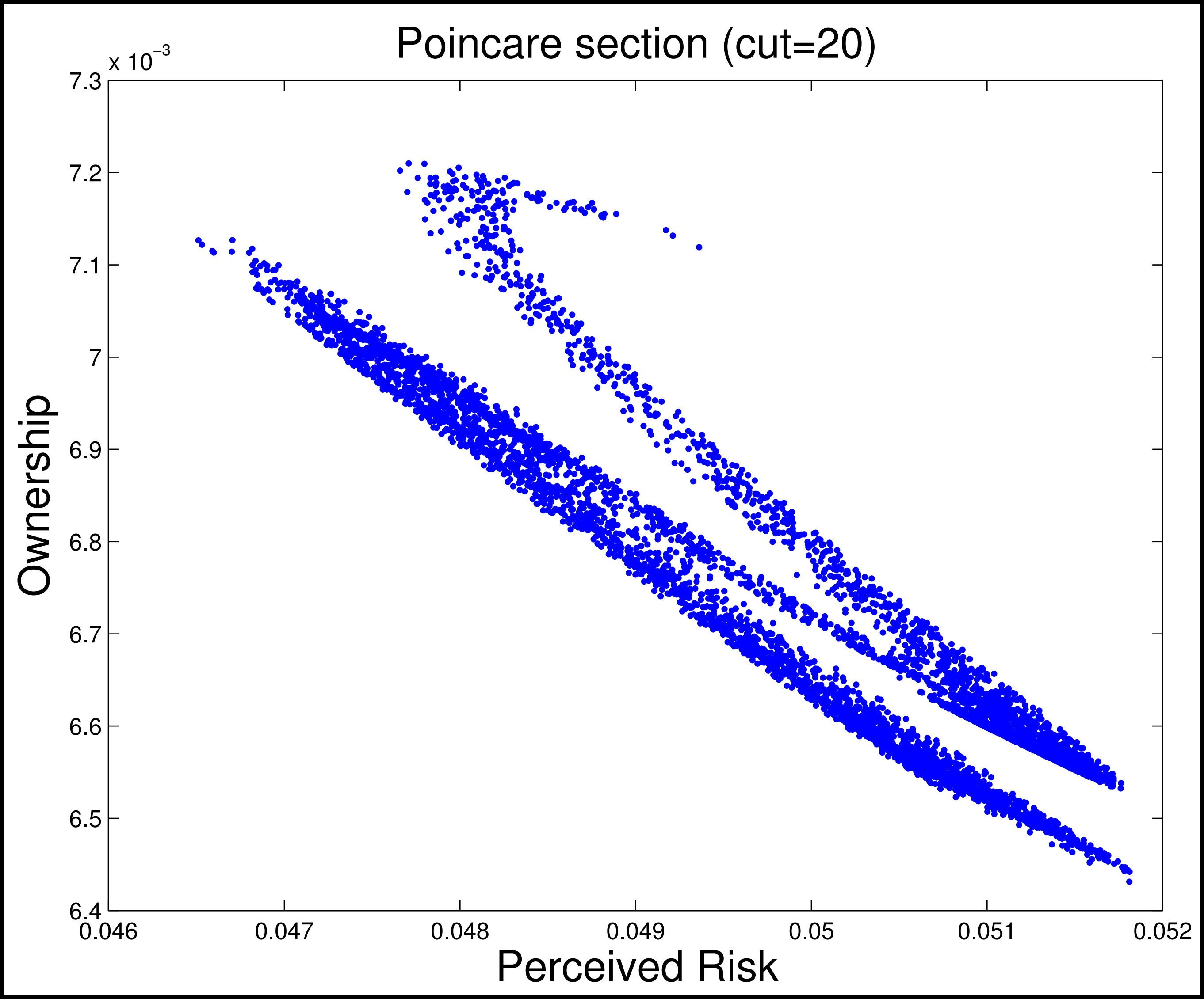
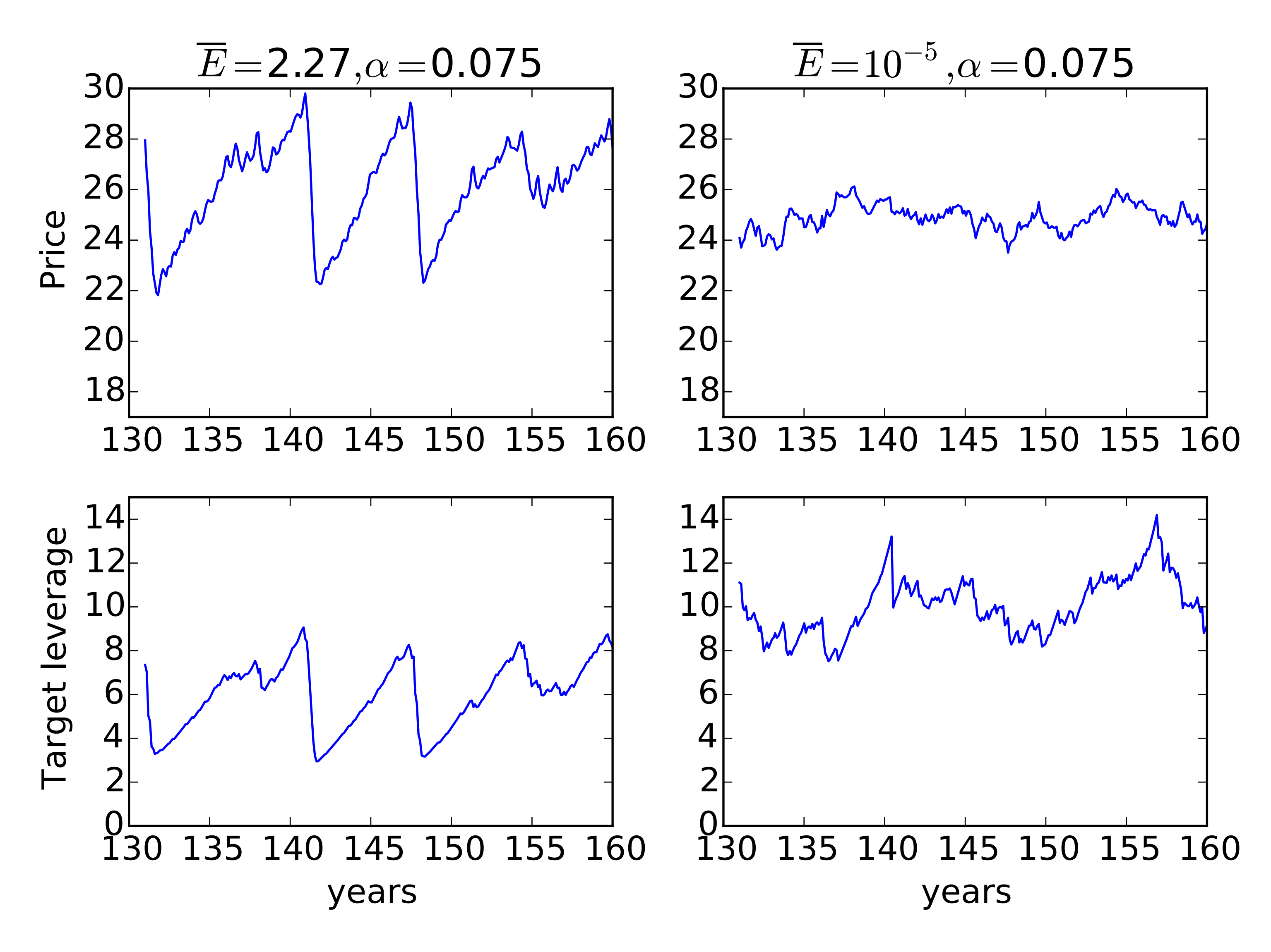
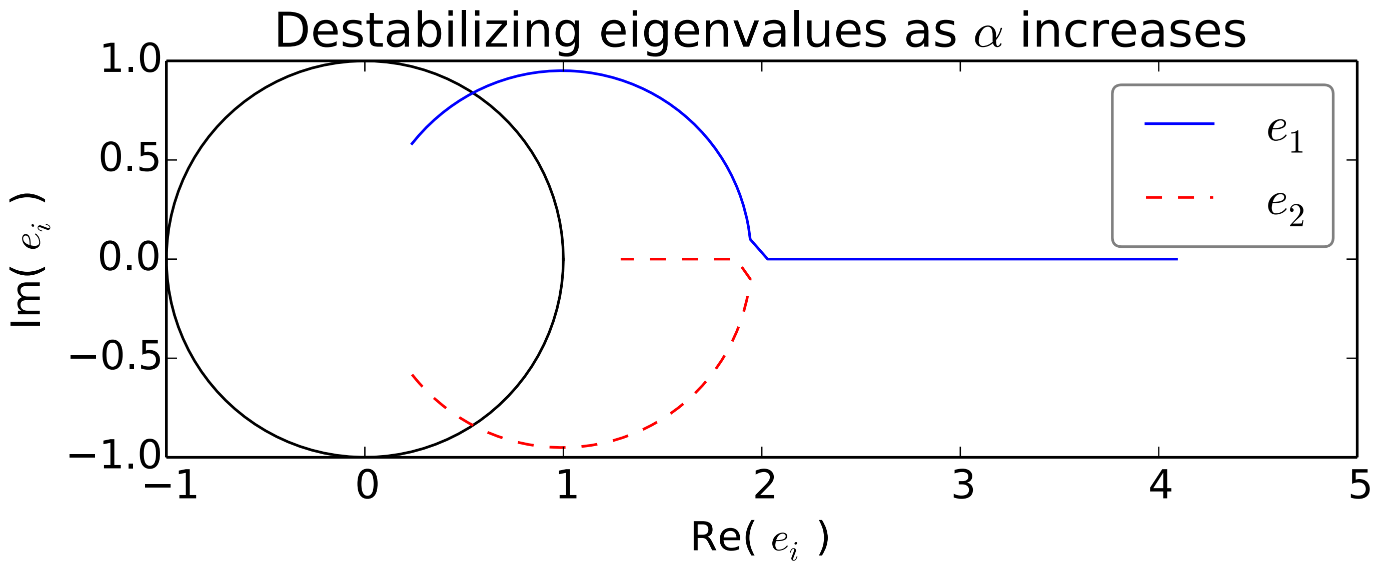


Poincare section (cut=20)
x 10^-3
7.3
7.2
7.1
7
6.9
6.8
6.7
6.6
6.5
6.4
Ownership
0.046
0.047
0.048
0.049
0.05
0.051
0.052
Perceived Risk


$\overline{E} = 2.27, \alpha = 0.075$
$\overline{E} = 10^{-5}, \alpha = 0.075$
Price
Target leverage
years
years

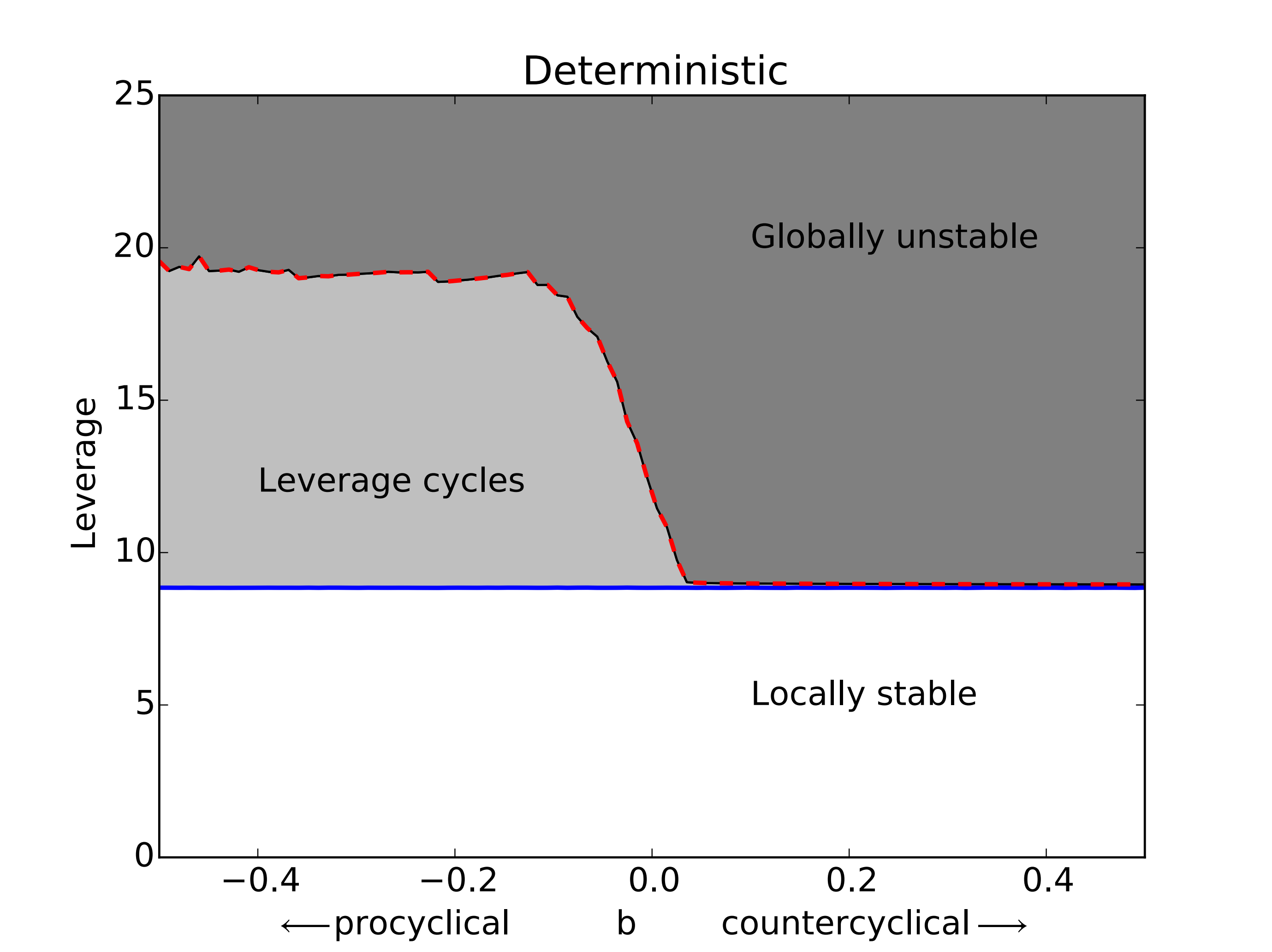


Destabilizing eigenvalues as α increases
1.0
0.5
0.0
−0.5
−1.0
−1
0
1
2
3
4
5
Im(e_i)
Re(e_i)
e_1
e_2

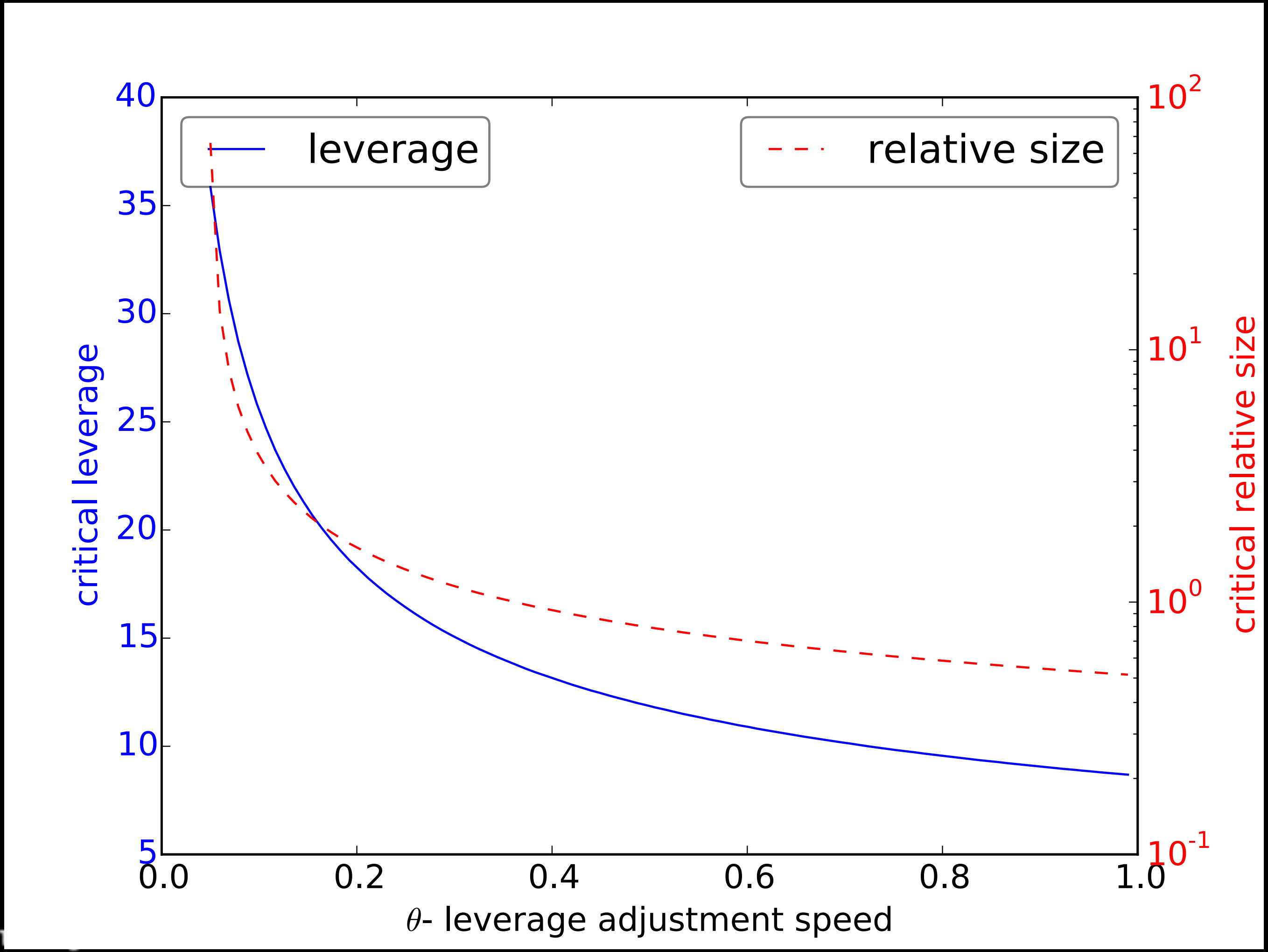
Key parameters

- 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

Bifurcation diagram



Stabilizing effect of slower adjustment



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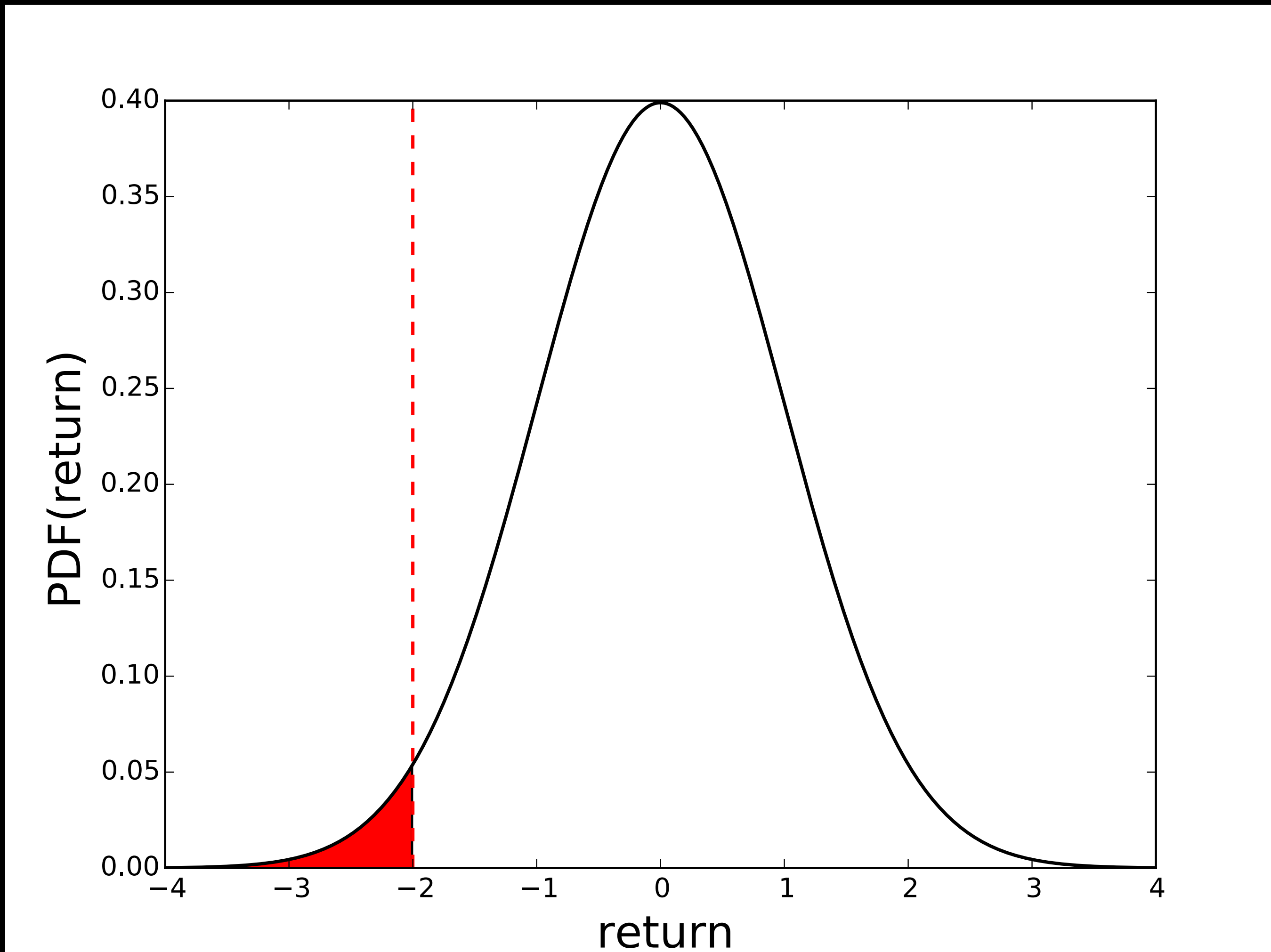
How to measure performance of leverage policy?

- We seek the policy that maximizes average leverage for a given average risk
- Use *realized shortfall* to measure risk
  - Defined as average loss in the tail
  - Realized version of Basel 3's "expected shortfall"
  - computed by taking average of losses over long simulation

Realized shortfall



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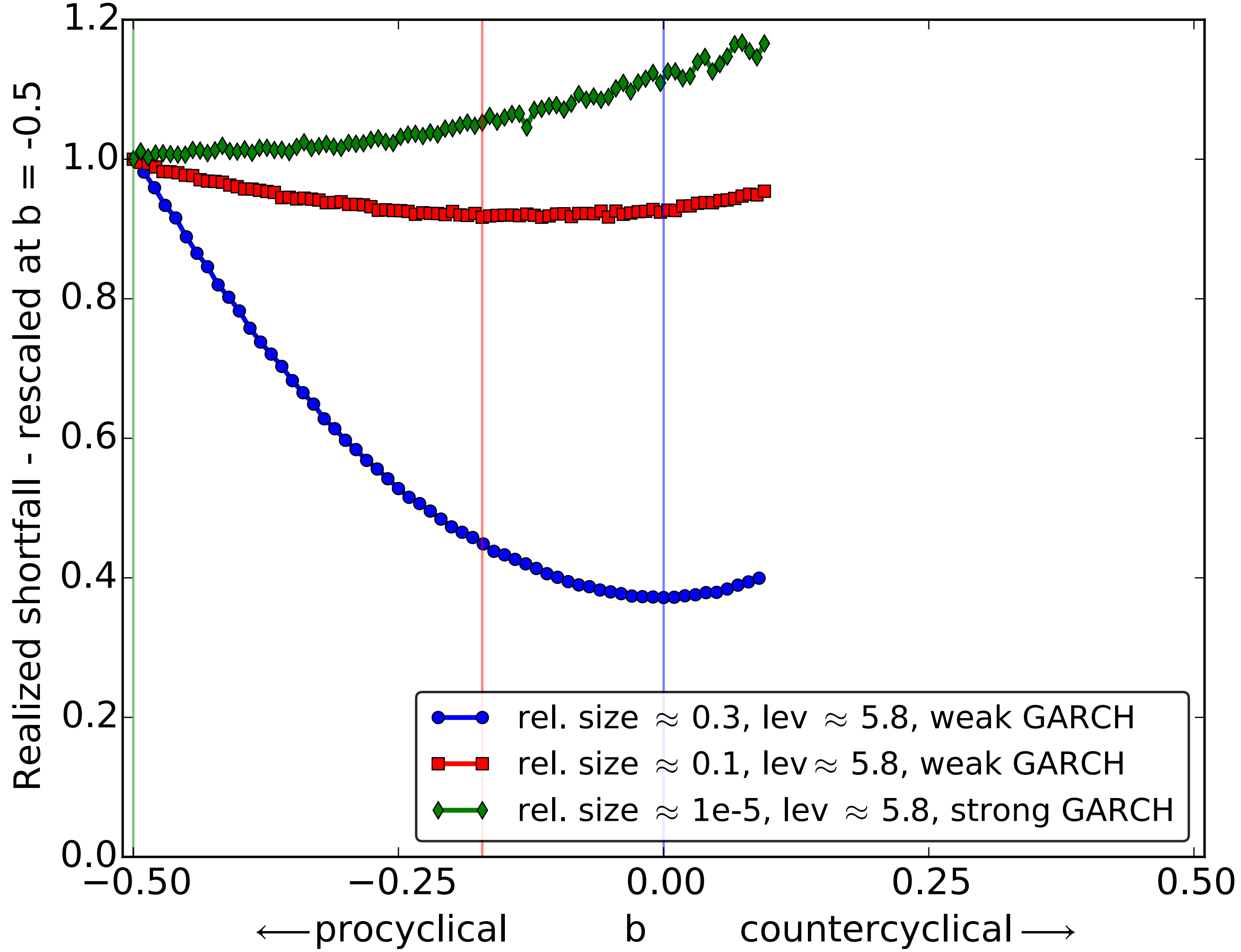
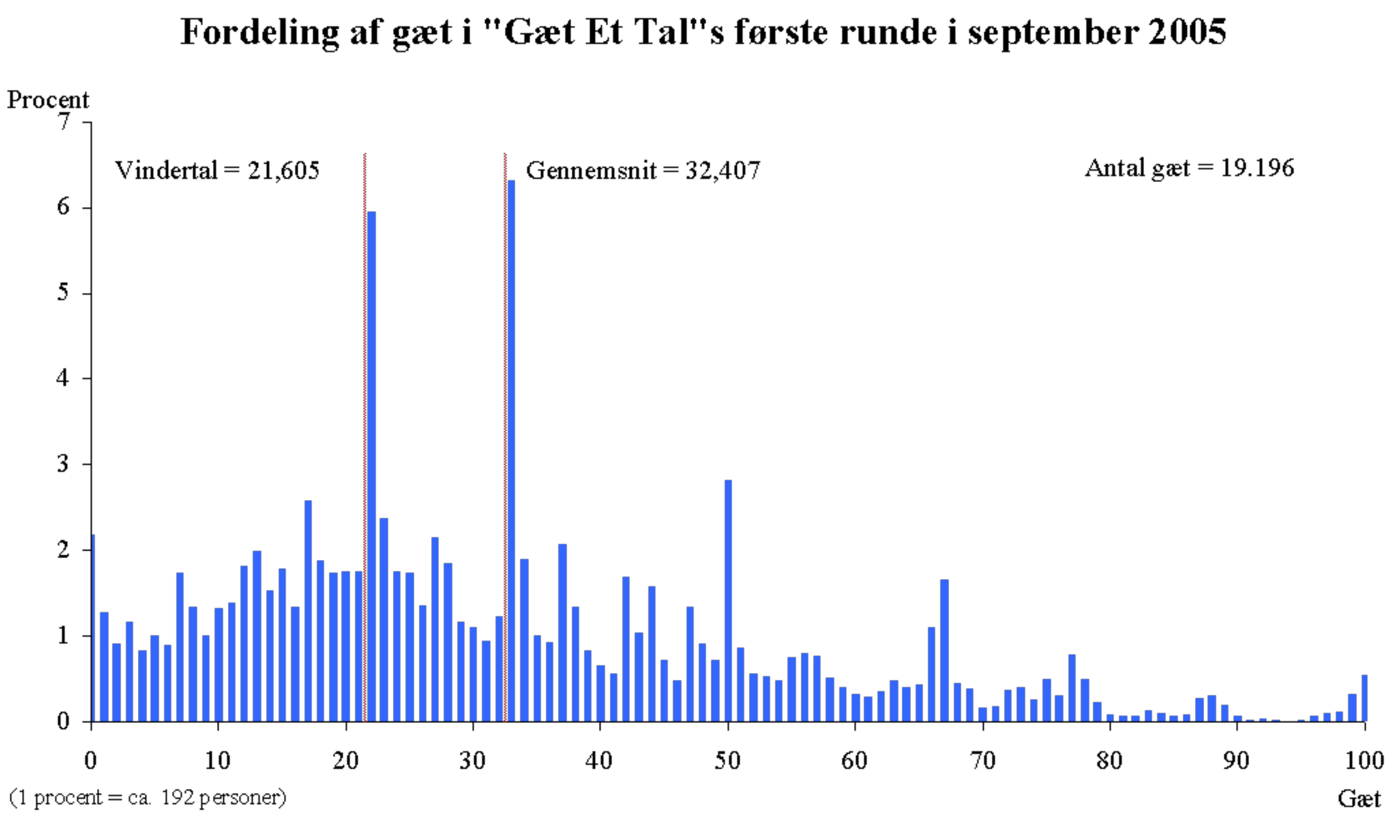

1.2
1.0
0.8
0.6
0.4
0.2
0.0
Realized shortfall - rescaled at b = -0.5
−0.50
−0.25
0.00
0.25
0.50
⟵procyclical
b
countercyclical⟶
rel. size ≈ 0.3, lev ≈ 5.8, weak GARCH
rel. size ≈ 0.1, lev ≈ 5.8, weak GARCH
rel. size ≈ 1e-5, lev ≈ 5.8, strong GARCH

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



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.

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

Back to agent-based modeling in general

Why isn't ABM the mainstay of economics?

- Math culture is deeply rooted
  - papers scored too much on math vs. science
  - disdain and distrust of simulation
  - fascination with rationality and optimality
- ABM is a fringe activity, hasn't delivered home runs needed to enter establishment
  - contrast to behavioral economics
  - chicken/egg problem
- Lucas critique

Paul Krugman's view of agent-based modeling

"Oh, and about ~~Roger~~Doyne Farmer (sorry, Roger!) and Santa Fe and complexity and all that: I was one of the people who got all excited about the possibility of getting somewhere with very detailed agent-based models — but that was 20 years ago. And after all this time, it's all still manifestos and promises of great things one of these days."

Paul Krugman, Nov. 30, 2010, in response to an article about INET housing project in WSJ.

Lucas Critique

- Recession of 70's. "Keynesian" econometric models.
- Phillips curve: Rising prices ~ rising employment
- Following Keynesians, Fed inflated money supply
- Result: Inflation, high unemployment = stagflation
- Problem: People can think
- Conclusion: Macro economic models must incorporate human reasoning
- Solution: Dynamic Stochastic General Eq. models

Structure vs. strategy

- Strategy: Agent decision making
- Stucture: Structural constraints on decision making, e.g. institutions, environment, accounting, social networks, …
- Can't model everything at once: Inherent tradeoff between structure and strategy.

Advantages of DSGE

- "Micro-founded" (unlike econometric models)
  - can be used for policy analysis.
- Time series models
  - initializable in current state of the world, can make conditional forecasts
- Describe a specific economy at a specific time.
- In some sense parsimonious

Why agent-based modeling?

- Diversifies toolkit of economics: Complements DSGE and econometric models.
- Time is ripe: increased computer power, Big Data, behavioral knowledge. Never let a crisis go to waste.
- Hasn't really been tried yet -- crude estimates:
  - econometric models: 30,000 person-years
  - DSGE models: 20,000 person-years
  - agent-based models: 500 person-years
- Successes elsewhere: Traffic, epidemiology, defense
- Examples of successes in economics:
  - Endogenous explanations of clustered volatility and heavy tails; firm size; neighborhood choice

Advantages

- Can faithfully represent real institutions
- Easily captures instabilities, feedback, nonlinearities, heterogeneity, network structure,...
- Shocks can be modeled endogenously
- Easy to do policy testing
- Easy to incorporate behavioral knowledge
- Can calibrate modules independently using micro data -- much stronger test of models!
  - In some sense between theory and econometrics
- ABMs synthesize knowledge:
  - Possible to understand what is not understood

Challenges

- Little prior art
- Developing appropriate abstractions
  - What to include, what to omit?
  - How to keep model simple yet realistic?
- Micro-data to calibrate decision rules?
- Data censoring problems
- Realistic agent-based models are complicated.
- No theoretical foundation

Cautionary tale of weather forecasting

Design philosophy

- As simple as possible (but no more)
- Design model around available data
- Fit modules and agent behaviors independently from target data, using several different methods:
  - micro-data for calibration and testing
  - consult domain experts for behavioral hypotheses
  - adaptive optimization to cope with Lucas critique
  - economic experiments
- Systematically explore model sensitivities
- Plug and play
- Standardized interfaces
- Industrial code, software standards, open source

Formulating decision rules

- Make something up
- Take from behavioral literature
- Perform experiments in context of ABM
- Interview domain experts
- Calibrate against microdata
- Learning and selection, Lucas critique
- Rationality

Existing ABMS in economics

- All are qualitative
- Range of complexity, e.g.
  - zero/low intelligence continuous double auction
  - latent order book (Bouchaud group)
  - Lebaron, Brock Hommes trend follow/fundamentalist
  - Axtell firm size
  - Thurner et al. leveraged value investors
  - SFI Stock Market
  - Dosi-group
  - EURACE

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

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.

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

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

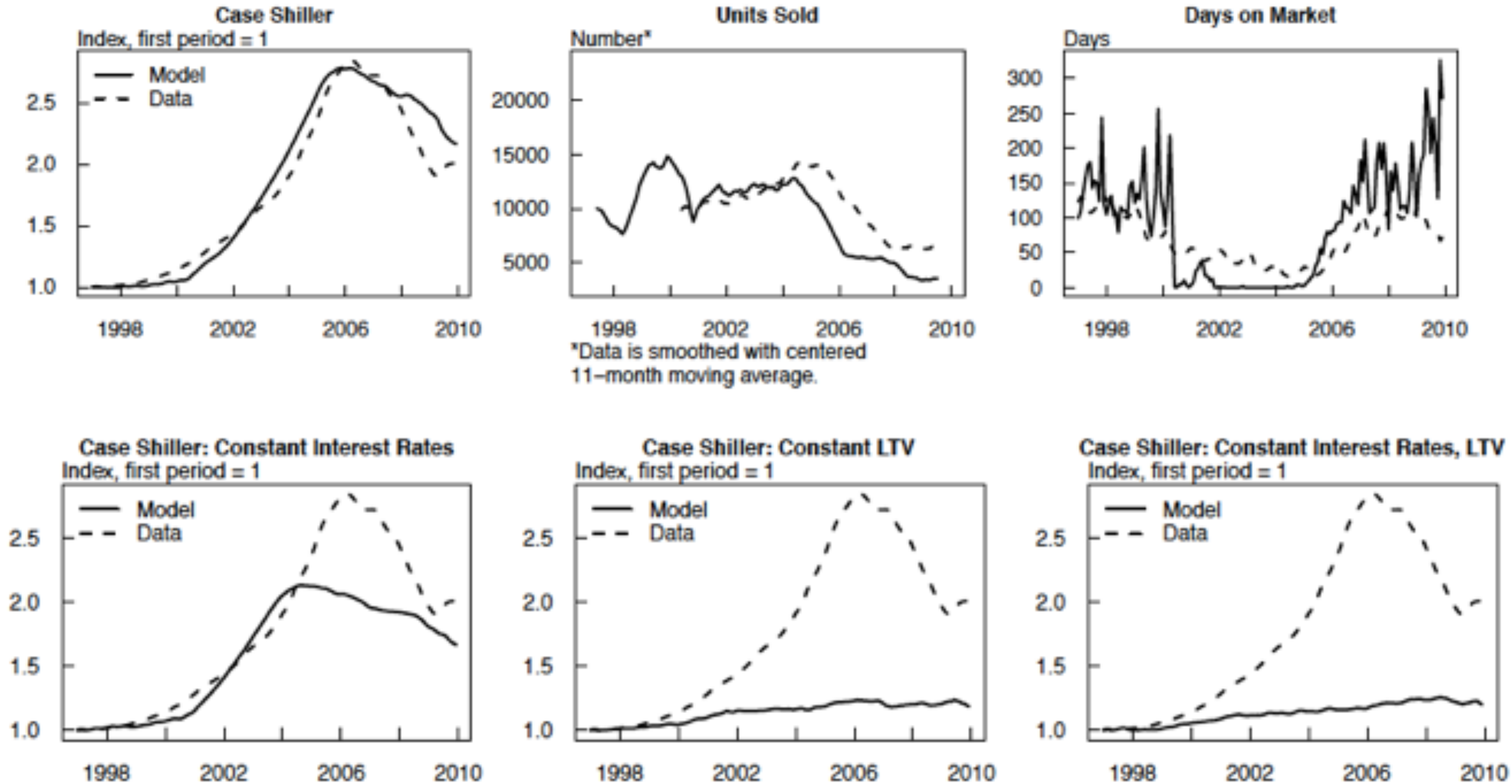
Housing model algorithm

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



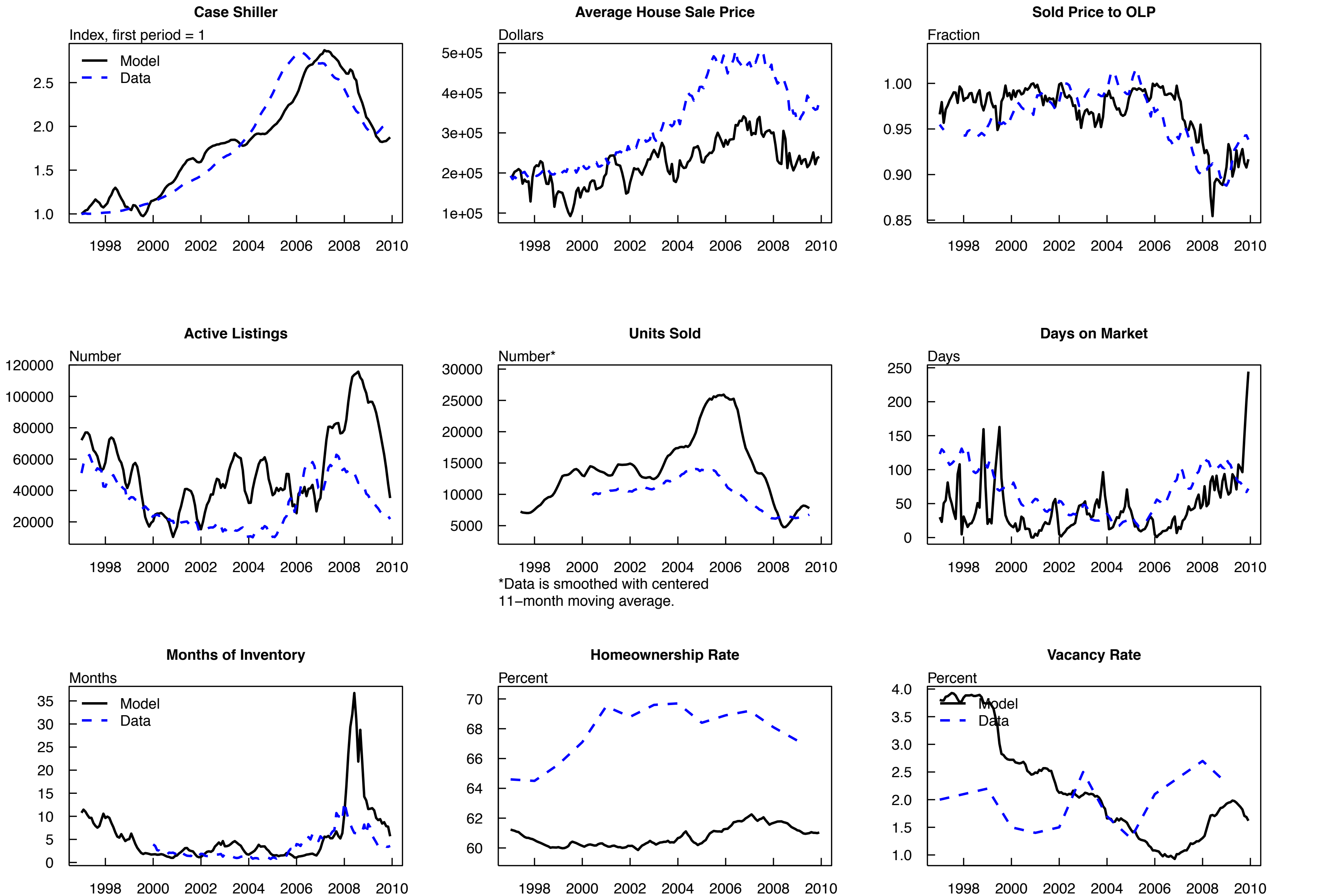
(this is an early slide)

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.

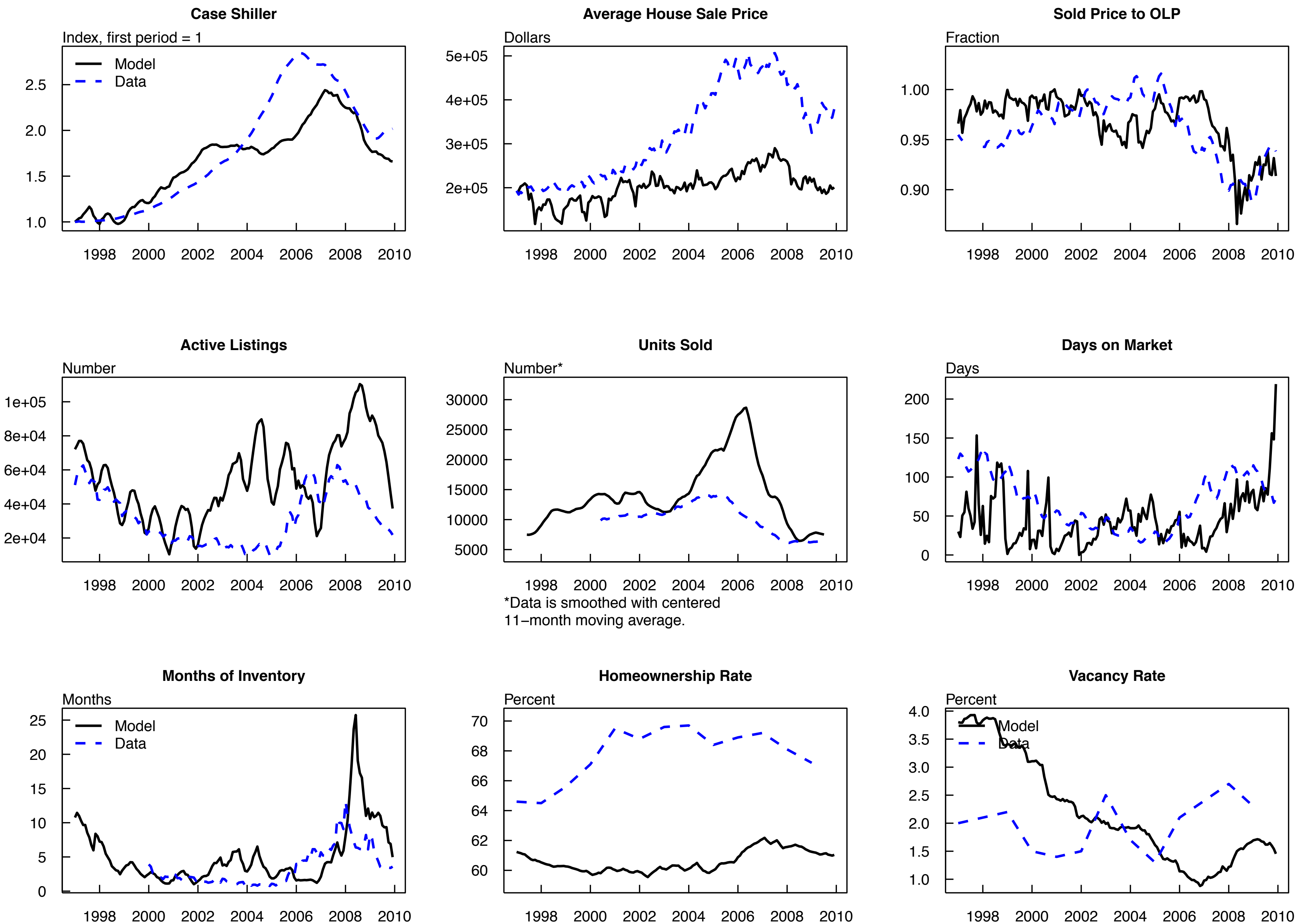
Baseline result

Housing Market Results



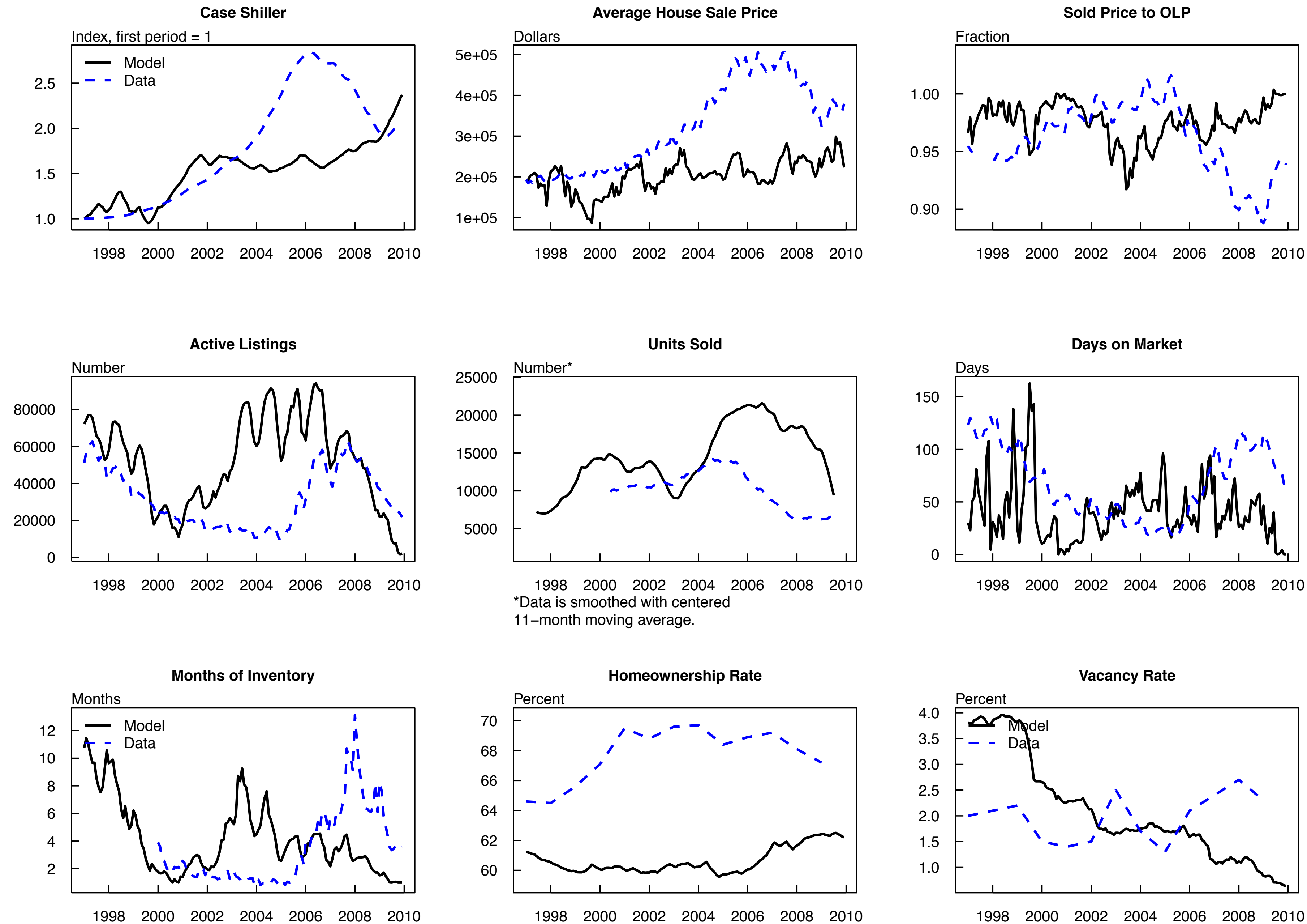
fixed interest rate

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?