# Computational Tools and Techniques for Numerical Macro-Financial Modeling

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MFM/BFI

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(MFM/BFI) March 7, 2017 1 / 23

# Numerical Building Blocks

### Spectral approximation technology:

numerical computation in Chebyshev functions

piece-wise smooth functions breakpoints detection

rootfinding

functions with singularities

fast adaptive quadratures

continuous QR, SVD, least-squares

linear operators

solution of linear and non-linear ODE

Fréchet derivatives via automatic differentiation

PDEs in one space variable plus time

#### Stochastic processes:

(quazi) Monte-Carlo simulations, Polynomial Expansion (gPC), finite-differences (FD)

non-linear IRF

Borovička-Hansen-Sc[heinkman shock-exposure and shock-price elasticities

Malliavin derivatives

#### Many states:

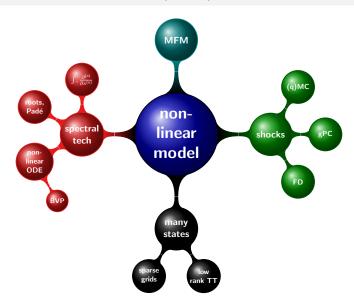
Dimensionality Curse Cure

low-rank tensor decomposition

sparse Smolyak grids

(MFM/BFI) March 7, 2017 2 / 23

# Numerical Building Blocks (cont.)



(MFM/BFI) March 7, 2017 3 / 23

# Horse race: methods and models

#### models

He-Krishnamurthy, "Intermediary Asset Pricing"

Klimenko-Pfeil-Rochet-DeNicolo, "Aggregate Bank Capital and Credit Dynamics"

Brunnermeier-Sannikov, "A Macroeconomic Model with a Financial Sector"

Basak-Cuoco, "An Equilibrium Model with Restricted Stock Market Participation"

Di Tella, "Uncertainty Shocks and Balance Sheet Recessions"

#### methods

spectral technology vs discrete grids

Monte-Carlo simulations (MC) vs Polynomial Expansion (gPC) vs finite-differences SPDE (FD)

Smolyak sparse grids vs tensor decomposition

#### criteria

elegance: clean primitives, libraries, ease of mathematical concepts expression in code speed: feasibility, ready prototypes, LEGO blocks; precision: numerical tests of speed vs stability trade-offs common metrics: shock exposure elasticity, asset pricing implications

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# shock-exposure and shock-price elasticity first kind

Multiplicative functional  $M_t$ :

- 1) consumption  $C_t$  for consumption shock-exposure
- 2) stochastic discount factor  $S_t$  for consumption shock-price elasticity

$$d \log M_t = \beta(X_t)dt + \alpha(X_t)dB_t$$

$$\epsilon(x, t) = \sigma(x) \frac{\partial}{\partial x} \log \mathbb{E}[M_t | X_0 = x] + \alpha(x)$$

Define

$$\phi(x, t) = \mathbb{E}\left[\frac{M_t}{M_0} | X_0 = x\right]$$

Then solve PDE

$$\frac{\partial \phi(x,t)}{\partial t} = \frac{1}{2}\sigma^2(x)\frac{\partial^2}{\partial x^2}\phi(x,t) + \left(\mu(x) + \sigma(x)\alpha(x)\right)\frac{\partial}{\partial x}\phi(x,t) + \left(\beta(x) + \frac{1}{2}|\alpha(x)^2|\right)\phi(x,t)$$

s.t. initial boundary condition  $\phi(x,0)=1$ 

# shock-exposure and shock-price elasticity second kind

Multiplicative functional  $M_t$ :

- 1) consumption Ct for consumption shock-exposure
- 2) stochastic discount factor  $S_t$  for consumption shock-price elasticity

$$d \log M_t = \beta(X_t)dt + \alpha(X_t)dB_t$$

The elasticity of second kind is

$$\epsilon_2(X_t) = \frac{\mathbb{E}(\mathfrak{D}_t \ M_t) | \mathcal{F}_0}{\mathbb{E} M_t | \mathcal{F}_0}$$

Use specification for  $M_t$  to get

$$\epsilon_2(X_t) = \frac{\mathbb{E}(\ M_t \eta(X_t) \alpha(X_t)) | \mathcal{F}_0}{\mathbb{E} M_t | \mathcal{F}_0}$$

Then solve PDE twice

$$\frac{\partial \phi(x,t)}{\partial t} = \frac{1}{2}\sigma^2(x)\frac{\partial^2}{\partial x^2}\phi(x,t) + \left(\mu(x) + \sigma(x)\alpha(x)\right)\frac{\partial}{\partial x}\phi(x,t) + \left(\beta(x) + \frac{1}{2}|\alpha(x)^2|\right)\phi(x,t)$$

s.t. initial boundary condition  $\phi(x,0)=1$  to get a solution  $\phi_1(x,t)$  and initial boundary condition  $\phi(x,0)=\alpha(x)$  to get a solution  $\phi_2(x,t)$  Then, second type elasticity is

$$\epsilon_2(x, t) = \frac{\phi_2(x, t)}{\phi_1(x, t)}$$

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#### "Intermediary Asset Pricing": Zhiguo He and Arvind Krishnamurthy, AER, 2013

Find 
$$\frac{P_t}{D_t} = F(y), \ \forall y \in \left[0, \frac{1+l}{\rho}\right]$$
, by solving

$$\begin{split} F^{\prime\prime\prime}\left(y\right)\theta_{s}\left(y\right)G\left(y\right)^{2}\frac{\left(\theta_{b}\left(y\right)\sigma\right)^{2}}{2}\frac{G\left(y\right)}{\theta_{s}\left(y\right)F\left(y\right)}\left(\frac{1+I+\rho y(\gamma-1)}{1+I-\rho y+\rho \gamma G\left(y\right)\theta_{b}\left(y\right)}\right)\\ &=\rho+g(\gamma-1)-\frac{1}{F\left(y\right)}+\frac{\gamma\left(1-\gamma\right)\sigma^{2}}{2}\left(1+\frac{\rho G\left(y\right)\theta_{b}\left(y\right)}{1+I-\rho y}\right)\frac{y-G\left(y\right)\theta_{b}\left(y\right)}{\theta_{s}\left(y\right)F\left(y\right)}\left[\frac{1+I-\rho y-\rho G\left(y\right)\theta_{b}\left(y\right)}{1+I-\rho y+\rho \gamma G\left(y\right)\theta_{b}\left(y\right)}\right]\\ &-\left(\frac{\left(1+I-\rho y\right)\left(G\left(y\right)-1\right)}{\theta_{s}\left(y\right)F\left(y\right)}+\gamma \rho G\left(y\right)\right)\frac{\theta_{s}\left(y\right)+I+\theta_{b}\left(y\right)\left(g\left(\gamma-1\right)+\rho\right)-\rho y}{1+I-\rho y+\rho \gamma G\left(y\right)\theta_{b}\left(y\right)}. \end{split}$$

where

$$G(y) = \frac{1}{1 - \theta_{S}(y)F'(y)},$$

and

|                 | if $y \in (0, y^c)$                       | if $y \in \left(y^c, \frac{1+l}{\rho}\right)$ |
|-----------------|---|---|
| $\theta_s(y) =$ | $\frac{(1-\lambda)y}{F(y)-\lambda y}$     | $\frac{m}{1+m}$                               |
| $\theta_b(y) =$ | $\lambda y \frac{F(y)-y}{F(y)-\lambda y}$ | $y - \frac{m}{1+m}F(y)$                       |

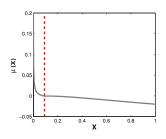
The endogenous threshold  $y^c$  is determined by  $y^c = \frac{m}{1-\lambda+m}F(y^c)$ . Boundary conditions on y=0 and  $y=\frac{1+l}{r}$ .

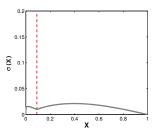
$$F\left(0\right) = \frac{1+F'\left(0\right)I}{\rho+g\left(\gamma-1\right)+\frac{\gamma\left(1-\gamma\right)\sigma^{2}}{2}-\frac{I\gamma\rho}{1+I}};\ F\left(\frac{1+I}{\rho}\right) = \frac{1+I}{\rho};\ F'\left(\frac{1+I}{\rho}\right) = 1.$$

## He-Krishnamurthy, BVP solution

$$\begin{split} dX_t &= \mu_y(X_t)dt + \sigma_y(X_t)dB_t, X_t = \frac{w_t}{P_t}; \ \sigma_y(X_t) = -\frac{\theta_b}{1 - \theta_s F'(y)}\sigma; X_t = \frac{F(y) - y}{F(y)} \\ d\log C_t &= \beta(X_t)dt + \alpha(X_t)dB_t; d\log S_t = -\gamma \log C_t \end{split}$$

$$\beta(x) = \mu(x)\xi(x) + \frac{1}{2}\sigma(x)^2\frac{\partial\xi}{\partial x} + g_d - \frac{\sigma_d^2}{2}; \\ \alpha(x) = \sigma(x)\xi(x) + \sigma_d; \\ \xi(x) = -\rho\frac{\rho'(x)(1-x) - \rho(x)}{1+I-\rho(1-x)\rho(x)}$$

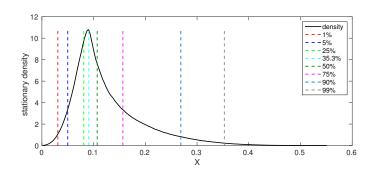




8 / 23

#### example, He-Krishnamurthy

# stationary density distribution, percentiles



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(MFM/BFI) March 7, 2017 9 / 23

#### Adaptive Chebyshev functional approximation (chebfun.org)

Given Chebyshev interpolation nodes  $z_k,\,k=1,\ldots,m$  on [-1,1]

$$z_k = -\cos\left(\frac{2k-1}{2m}\pi\right)$$

and Chebychev coefficients  $a_i, i=0,\ldots,n$  computed on Chebychev nodes we can approximate

$$\mathbb{F}(x) \approx \sum_{i=0}^{n} a_{i} T_{i}(x); a_{i} = \frac{2}{\pi} \int_{-1}^{1} \frac{\mathbb{F}(x) T_{i}(x)}{\sqrt{1-x^{2}}} dx$$

Chebyshev interpolation nodes and degree of polynomials have to be adaptive during continuous Newton updates.

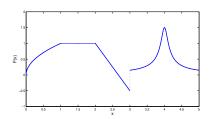
- (i) When in doubt, use Chebyshev polynomials unless the solution is spatially periodic, in which case an ordinary Fourier series is better.
- (ii) Unless youre sure another set of basis functions is better, use Chebyshev polynomials.
- (iii) Unless youre really, really sure that another set of basis functions is better, use Chebyshev polynomials

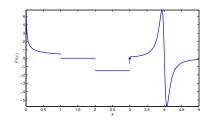
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<sup>&</sup>quot;Approximation Theory and Approximation Practice", by Lloyd N. Trefethen (chebfun.org)

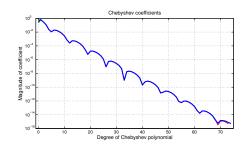
<sup>&</sup>quot;Chebyshev and Fourier Spectral Methods", by John P. Boyd

#### Adaptive Chebyshev functional approximation: examples (chebfun)

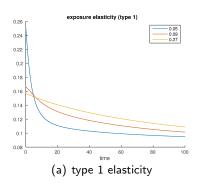


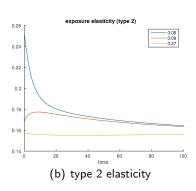


11 / 23



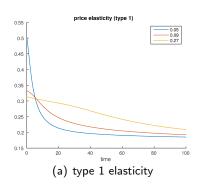
# He-Krushnamurthy: shock exposure, specialist C

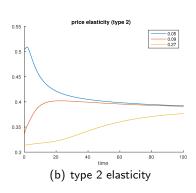




12 / 23

## He-Krushnamurthy: price exposure, specialist C





(MFM/BFI) March 7, 2017 13 / 23

# Brunnermeier-Sannikov example

$$\frac{dX_t}{X_t} = \mu(X_t)dt + \sigma(X_t)dB_t - d\zeta_t, X_t = \frac{N_t}{q_t K_t};$$

X(t): expert share of wealth

Consumption is aggregate output net of aggregate investment

$$C_t^a = [a\psi(X_t) + \underline{a}(1 - \psi(X_t))]K_t$$

$$d \log C_t = \beta(X_t)dt + \alpha(X_t)dB_t;$$

where

$$\alpha(X) = \sigma; \beta(X) = \Phi(X) - \delta - \sigma^2/2$$

For log-utility

$$S_t/S_0 = \mathbf{e}^{-\rho t} C_0/C_t$$

### Brunnermeier-Sannikov: shock exposure, aggregate C

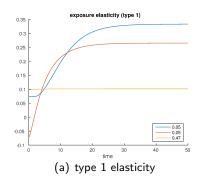
for logarithmic utility consumption of both households and experts are myopic, proportional to their wealth  $N_t$ 

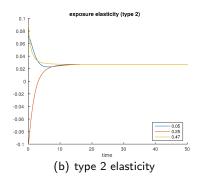
$$d\zeta_t = \rho dt$$
;  $d \log C_t = d \log K_t$ 

$$\text{d}\log K_t = \left(\Phi(i_t) - \delta \psi_t - \underline{\delta}(1-\psi_t) - \frac{1}{2}\sigma^2\right)\text{d}t + \sigma \text{d}B_t$$

for  $\delta = \delta$ 

$$\alpha(X) = \sigma; \beta(X) = \Phi(X) - \delta - \frac{1}{2}\sigma^2$$





15 / 23

## Brunnermeier-Sannikov: price exposure, aggregate C

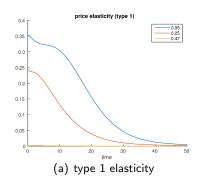
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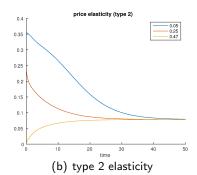
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for  $\delta = \underline{\delta}$ 

$$\alpha(X) = \sigma; \beta(X) = \Phi(X) - \delta - \frac{1}{2}\sigma^2$$





16 / 23

# Model Settings, Klimenko, Pfeil, Rochet, DeNicolo (KPRD)

State - equity EMultiplicative functional M = R(E)

$$dE_t = \mu(E_t)dt + \sigma(E_t)dB_t, p + r \le R_t \le R_{max},$$

where

$$\mu(E) = Er + L(R(E))(R(E) - r - p); \sigma(E) = L(R(E))\sigma_0.$$

$$\int_0^{E_{max}} \frac{R(s)-p-r}{\sigma_0^2 L(R(s))} ds = \ln(1+\gamma); u(E) = \exp\left(\int_E^{E_{max}} \frac{R(s)-p-r}{\sigma_0^2 L(R(s))} ds\right)$$

with

$$L(R) = \left(\frac{\overline{R} - R}{\overline{R} - p}\right)^{\beta}$$

where u(E) is market-to-book value

$$d \log R = \frac{R(E)'}{R(E)} dE = \psi(E) dE \rightarrow d \log R_t = \beta(E_t) dt + \alpha(E_t) dB_t$$

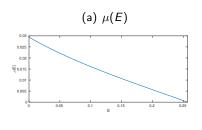
where 
$$\beta(E) = \mu(E)\psi(E) + \frac{1}{2}\sigma(E)^2\frac{\partial\psi(E)}{\partial E}$$
,  $\alpha(E) = \sigma(E)\psi(E)$ ; s.t. Neumann b.c.:  $\frac{\partial\phi_t(E)}{\partial x}\bigg|_{E_{min,max}} = 0$ 

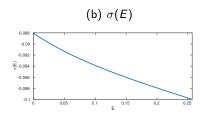
$$R'(E) = -\frac{1}{\sigma_0^2} \frac{2(\rho - r)\sigma_0^2 + [R(E) - \rho - r]^2 + 2rE[R(E) - \rho - r]L(R(E))^{-1}}{L(R(E)) - L'(R(E))[R(E) - \rho - r]}, R(E_{max}) = \rho + r$$

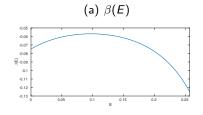
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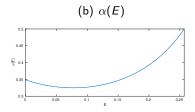
# State Space (E) drift $\mu(E)$ and volatility $\sigma(E)$ , functional $M: \alpha(E), \beta(E)$

Klimenko, Pfeil, Rochet, DeNicolo (KPRD), revised





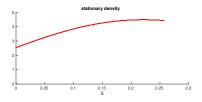




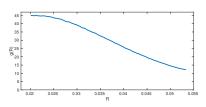
18 / 23

# stationary density in E and R, Klimenko, Pfeil, Rochet, DeNicolo (KPRD)

in E space

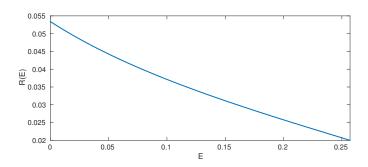


in R space (identical to a graph in KPRD paper)



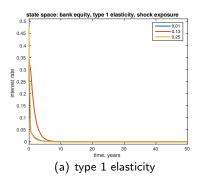
# R=R(E), Klimenko, Pfeil, Rochet, DeNicolo (KPRD)

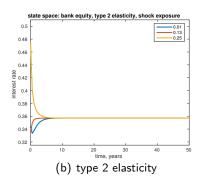




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# Shock-exposure elasticity for R = R(E) (KPRD)





21 / 23

# SDF and price elasticity, Klimenko, Pfeil, Rochet, DeNicolo (KPRD)

State - equity E

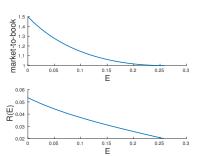
Multiplicative functional for SDF M = u(E)

$$u(E) = \exp\left(\int_{E}^{E_{max}} \frac{R(s) - p - r}{\sigma_0^2 L(R(s))} ds\right)$$

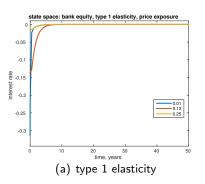
with

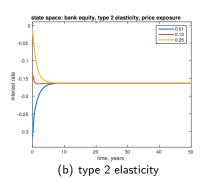
$$L(R) = \left(\frac{\overline{R} - R}{\overline{R} - p}\right)^{\beta}$$

where u(E) is market-to-book value



# Price elasticity for R = R(E) (KPRD)





23 / 23