### Smart SDFs

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### Overview

SDF Intro

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Nonparametric SDFs

### Stochastic Discount Factor

- Market with N assets. Sequence random vectors of prices  $\{p_t\}$  taking values on  $\mathbb{R}^N$
- Formally  $\{p_t\}$  is a sequence of random vectors defined on a Filtered Probability Space  $(\Omega, \mathcal{I}, \{\mathcal{I}_t\}, \mathbb{P})$

#### **SDF**

A SDF between period t and t+1 is a random variable  $m_{t,t+1}>0$  a.s. such that:

$$p_t = \mathbb{E}_t[m_{t,t+1}p_{t+1}].$$

## SDF - Economic justification

- Agent maximizes expected life-time utility from consumption:

$$\max_{\{c_t\},\{\theta_t\}} \mathbb{E}_0 \left[ \sum_{t=0}^{\infty} \beta^t U(c_t; \gamma) \right]$$
s.t. 
$$c_t + p_t^T \theta_t = p_t^T \theta_{t-1}$$

where  $\{\theta_t\}$  is a sequence of portfolio weights.

ullet First-order condition wrt  $heta_t$  and Law Iterated Expectations  $\Longrightarrow$ 

$$p_t = \mathbb{E}_t \left[ \beta \frac{U'(C_{t+1}; \gamma)}{U'(C_t; \gamma)} p_{t+1} \right]$$

## SDF - Financial justification

### Assumptions

- $p_{t+1}$  are  $\mathcal{I}_{t+1}$  measurable with finite conditional (on  $\mathcal{I}_t$ ) second moment.
- ② There exist a linear pricing functional  $\pi_{t,t+1}: p_{t+1} \mapsto p_t$  conditioned on  $\mathcal{I}_t$  and satisfies a conditional continuity restriction.
- **3** There is no arbitrage in the market: if  $0 \neq p_{t+1} \geq 0$  a.s., then  $p_t > 0$  a.s.

### Fundamental theorem of Asset Pricing

Given the previous assumptions, the Riesz representation theorem implies

$$\rho_t = \pi_{t,t+1}(\rho_{t+1}) = \mathbb{E}_t[m_t \rho_{t+1}]$$

where  $m_t > 0$  a.s. random variable.

# SDF - Cox's justification

#### Cox

All models are wrong, but some of them are useful.

#### Useful?

- Any asset pricing model (CAPM, Fama-French 3-factor model, ecc.)
   is a particular specification of the SDF
- SDF incorporates time discounting, preferences, risk discounting, ecc.
   (Specify a SDF model to identify these features)
- SDF carries information on economic outlook. "High" SDF ⇒
   "bad" economic outlook
- Trading strategy: sell financial portfolio replicating the SDF (see later)

### Parametric SDFs

### Economic specifications

 $m_{t,t+1} = m(Y_{t+1}; \alpha)$  where  $Y_{t+1}$  are relevant state variables and  $\alpha$  is a vector of parameters.

Time-separable preferences with CRRA utility

$$m_{t,t+1} = \beta (c_{t+1}/c_t)^{-\gamma}, \qquad \alpha = (\beta, \gamma)$$

• Time-nonseparable Epstein-Zin preferences

$$m_{t,t+1} = \beta^{\lambda} (c_{t+1}/c_t)^{-\gamma\lambda} (R_{t+1}^*)^{\lambda-1}, \qquad \alpha = (\beta, \gamma, \lambda)$$

### Parametric SDFs

### Financial specifications

Linear factor models:

$$m_{t,t+1} = \phi_0 + \phi_1^T F_{t+1}, \qquad \alpha = (\phi_0, \phi_1^T)$$

- CAPM:  $F_t = R_t^m$
- Fama French 3-factor model:  $F_t = (R_t^m, SMB_t, HML_t)^T$
- Exponentially affine factor models:

$$m_{t,t+1} = \exp(\phi_0 + \phi_1^T F_{t+1})$$

note that  $m_{t,t+1} > 0$  a.s.

### Parametric SDFs

#### Estimation

Two-step GMM estimator

$$\hat{\alpha}_T = \arg\min_{\alpha} \ \hat{g}_T(\alpha)^T \hat{V}_T^{-1} \hat{g}_T(\alpha)$$

where 
$$\hat{g}_T(\alpha) = \frac{1}{T} \sum_{t=1}^{T-1} g(p_{t+1}, p_t, z_t; \alpha)$$
,

$$g(p_{t+1}, p_t, z_t; \alpha) = z_t \otimes (m_{t,t+1}(\alpha)p_{t+1} - p_t),$$

 $z_t$  is a vector of instruments and  $\hat{V}_{\mathcal{T}}$  is a consistent estimator of  $V_0$ 

## Nonparametric SDF - Hansen et al. 1990s

### Assumptions

- $m, p' \in L_2, p \in L_1$
- no arbitrage opportunities: if  $\theta^T p' \ge 0$  and  $\theta^T p'$  has positive probability, then  $\theta^T p > 0$ .
- no redundancies in the securities: if  $\theta^T p' = \theta^{*T} p'$  and  $\theta^T p = \theta^{*T} p$ , then  $\theta = \theta^*$ .

### Proposition

#### Consider

$$\inf_{m \in L_2, \ m \ge 0} \left\{ \mathbb{E}[m^2/2] : p = \mathbb{E}[mp'] \right\},$$
$$\max_{\theta \in \mathbb{R}^N} \left\{ \theta^T p/2 - \mathbb{E}[(\theta^T p')^{+2}/2] \right\}.$$

Then

$$m^* = \theta^{*T} p'$$

# Nonparametric SDF - Contribution

### Assumptions

- $p \in L_1$ ,  $m \in L_a$  and  $p_i' \in L_b$  for each security i, where a and b are Hölder conjugate
- there exits SDF  $\bar{M}>0$  a.s. such that  $\|\mathbb{E}[mp']-p\|<\lambda$

### Proposition

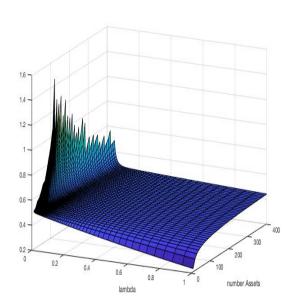
Consider

$$\inf_{m \in L_{a}, \ m \geq 0} \left\{ \ \mathbb{E}[\phi(m)] \ : \ \left\| \mathbb{E}[mp'] - p \right\| \leq \lambda \ \right\},$$
$$\max_{\theta \in \mathbb{R}^{N}} \left\{ \ \theta^{T} p - \phi_{+}^{c}(\theta^{T} p') - \lambda \left\| \theta \right\|^{*} \ \right\}.$$

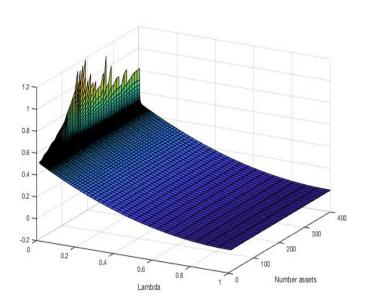
Then

$$m^* = (\phi_+^c)'(\theta^{*T}p')$$

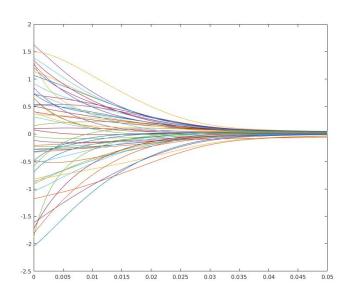
# Optimal value *l*<sub>2</sub>



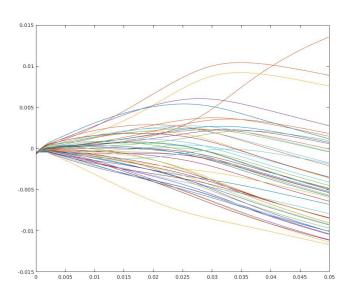
# Optimal value $l_1$



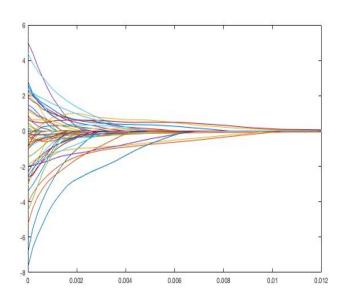
# Weights *l*<sub>2</sub>



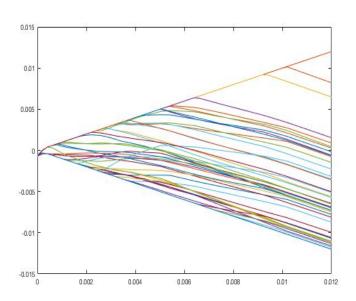
# Pricing errors *l*<sub>2</sub>



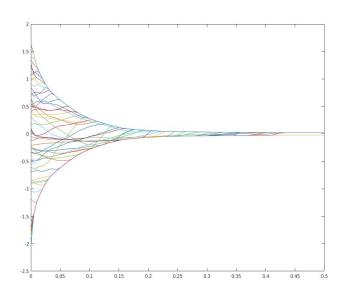
# Weights I<sub>1</sub>



# Pricing errors *l*<sub>1</sub>



# Weights $I_{\infty}$



# Pricing errors $I_{\infty}$

