

Discussion of:  
“Correcting Misspecified  
Stochastic Discount Factors”

by Raman Uppal, Paolo Zaffaroni, Irina Zviadadze

Christian Julliard

London School of Economics

# The big picture

An old idea:

- Asset returns are an adapted process to the SDF one.

⇒

- I. use returns to learn about the latent SDF.
- II. given a candidate SDF, use asset returns to estimate what the SDF is “missing”

**This paper:** focus on II assuming a linear factor structure for asset returns.

**In a nutshell:** construct a linear correction ( $\alpha$ -SDF) using the implied cross-sectional pricing errors of a candidate SDF (the  $\beta$ -SDF).

# HJ1: min variance SDF

Hansen-Jagannathan (1991 JPE):

## Definition (Canonical *HJ*-bound)

For each  $\mathbb{E}[M_t] = \bar{M}$ , the minimum variance SDF is

$$M_t^*(\bar{M}) \equiv \arg \min_{\{M_t(\bar{M})\}_{t=1}^T} \sqrt{\text{Var}(M_t(\bar{M}))} \text{ s.t. } \mathbf{0} = \mathbb{E}[\mathbf{R}_t^e M_t(\bar{M})] \quad (1)$$

where  $\mathbf{R}_t^e \in \mathbb{R}^N$ .

The solution to the above is  $M_t^*(\bar{M}) = \bar{M} + (\mathbf{R}_t^e - \mathbb{E}[\mathbf{R}_t^e])' \beta_{\bar{M}}$ , where  $\beta_{\bar{M}} = \text{Cov}(\mathbf{R}_t^e)^{-1} (-\bar{M} \mathbb{E}[\mathbf{R}_t^e])$ , and any candidate SDF  $M_t$  must satisfy  $\text{Var}(M_t(\bar{M})) \geq \text{Var}(M_t^*(\bar{M}))$ .

⇒  $M_t^* \equiv$  projection of true SDF on space of payoffs.

- Dimensionality of order  $N^2 \rightarrow$  problem with large  $N$ .

**Note:** violates non-negativity restriction (HJ1 provides a restricted one, but computationally more complex).



## HJ2: min variance correction to the SDF

Hansen-Jagannathan (1997 JF):

### Definition (HJ-correction)

Given a candidate SDF  $M_t$ :

$$d_{HJ}^2 \equiv \min_{q \in L^2} \mathbb{E} \left[ (M_t - q_t)^2 \right] \quad \text{s.t. } \mathbf{0} = \mathbb{E} [q_t \mathbf{R}_t^e].$$

- ⇒ HJ2 looks for the minimum (in a least square sense) linear adjustment that makes  $M_t - \theta' \mathbf{R}_t^e$  an admissible SDF (where  $\theta$  arises from the linear projection of  $M_t$  on the space of returns).
- Again, dimensionality of order  $N^2$  and violates non-negativity restriction.

# Changing measures

- Consider the vector of Euler equations

$$\mathbf{0} = \mathbb{E} \left[ \underbrace{m(\theta, t) \psi_t \mathbf{R}_t^e}_{M_t} \right] \equiv \int m(\theta, t) \psi_t \mathbf{R}_t^e dP$$

where  $m(\theta, t)$  is a known function of observable data,  $P$  is the physical probability measure, and  $\psi_t$  is an unobservable component.

- Under very weak regularity conditions, we have

$$\mathbf{0} = \int m(\theta, t) \frac{\psi_t}{\psi} \mathbf{R}_t^e dP = \int m(\theta, t) \mathbf{R}_t^e d\Psi = \mathbb{E}^\Psi [m(\theta, t) \mathbf{R}_t^e]$$

where  $\bar{x} := \mathbb{E}[x_t]$ , and  $\frac{\psi_t}{\psi} = \frac{d\Psi}{dP}$  is the Radon-Nikodym derivative.

**Note:**

- If  $m(\theta, t)$  is a constant,  $\Psi \equiv Q$
- if not,  $\psi$  is a multiplicative correction of the candidate sdf  $m$

# GJT: minimum entropy SDF and correction

Ghosh, Julliard, Taylor (2016 RFS):

## Definition (GJT-SDF)

Given an  $m(\theta, t)$  and a returns data, estimate the  $\Psi$  measure as

$$\hat{\Psi} = \arg \min_{\Psi} D(\Psi || P) \equiv \arg \min_{\Psi} \int \frac{d\Psi}{dP} \ln \frac{d\Psi}{dP} dP \text{ s.t. } \mathbf{0} = \int m(\theta, t) \mathbf{R}_t^e d\Psi$$

⇒ KLIC minimization under the asset pricing restriction.

- Since relative entropy is not symmetric, we can also use  $D(P || \Psi)$ .
- Dimensionality of order  $N$ , and guarantees non-negativity.
- ML interpretation and properties.
- HJ1/HJ2 as approximations/particular cases.
- $\psi$  adds minimum amount of additional info needed to price assets.

**Note:** correction is not necessarily orthogonal to  $m$ . And not, in the data, for consumption based models.

Out-of-sample (GJT 2018): prices assets (equities, commodities, currencies...) better than usual factors, and delivers the maximum Sharpe ratio returns (e.g. better than  $1/N$ , momentum+value etc.).

## $\psi$ correction à la HJ1

### Definition ( Volatility bound for $\psi_t$ )

For each  $E[\psi_t] = \bar{\psi}$ , the minimum variance  $\psi_t$  is

$$\psi_t^*(\bar{\psi}) \equiv \arg \min_{\{\psi_t(\bar{\psi})\}_{t=1}^T} \sqrt{\text{Var}(\psi_t(\bar{\psi}))} \text{ s.t. } \mathbf{0} = \mathbb{E}[\mathbf{R}_t^e m(\theta, t) \psi_t(\bar{\psi})].$$

The solution of the above minimization for a given  $m(\theta, t)$  is

$$\psi_t^*(\bar{\psi}) = \bar{\psi} + (\mathbf{R}_t^e m(\theta, t) - \mathbb{E}[\mathbf{R}_t^e m(\theta, t)])' \beta_{\bar{\psi}}$$

where  $\beta_{\bar{\psi}} = \text{Var}(\mathbf{R}_t^e m(\theta, t))^{-1} (-\bar{\psi} \mathbb{E}[\mathbf{R}_t^e m(\theta, t)])$

$\Rightarrow \psi_t^* \equiv \text{projection on space of } \underline{\text{scaled payoffs.}}$

**Note:** correction is not necessarily orthogonal to  $m$

## ... just one more factor

**Note:** in population or in sample, we are **always one factor away from perfect pricing** (e.g. MacKinlay (1995))

**Example:** consider a model with, as observable factors,  $k$  assets with excess returns in vector  $z_{p,t}$

$$\mathbf{R}_t^e = \alpha + Bz_{p,t} + \epsilon_t$$

$$\mathbb{E}\epsilon_t = 0, \quad \text{Var}[\epsilon_t] = \sum_{N \times N}, \quad \mathbb{E}z_{p,t} = \mu_p, \quad \text{Var}[z_{p,t}] = \Omega_{K \times K}, \quad \text{cov}[z_{p,t}, \epsilon_t] = 0$$

The efficient portfolio of the residual assets is then characterized by

- weights:  $\Sigma^{-1}\alpha$
- return:  $R_{h,t}^e \propto \epsilon_t' \Sigma^{-1} \alpha$  i.e.  $\perp z_{p,t}$
- squared SR:  $s_h^2 \equiv \alpha' \Sigma^{-1} \alpha$

⇒ adding this portfolio as a factor we achieve perfect pricing.

**This paper:** add the linear correction  $\epsilon_t' \Sigma^{-1} \alpha$  to the SDF ( $\alpha$ -SDF).

**Note:** dimensionality is still  $N^2$ , and still violates non-negativity... but good properties as  $N \rightarrow \infty$  (under some sort of weighted square integrability of the betas assumption)... but paper never use the limiting results in estimation...



# So, what's new here?

⇒ structure on  $\alpha$ :

$$\alpha = a + A\lambda_{miss} \text{ s.t. } a'\Sigma^{-1}a \leq \delta < \infty \quad \forall N$$

where  $A$  and  $\lambda_{miss}$  are, respectively, the loading and risk premia of the missing factors (identified by the diverging eigenvalues of  $\Sigma$  as  $N \rightarrow \infty$ ).

**But:** that's the “extended APT” of Uppal and Zaffaroni (2017)... say it!

So, what's really new here? ... I think: how to estimate the missing factors... But:

- ① that's only in Appendix E!
- ② that's only via Q-MLE (i.e. consistent but not efficient)
- ③  $N^2$  order of dimensionality (no use of limit results)
- ④ that's (presented at least) only for the case in which observable and latent factors are orthogonal...

**Note:** the latter is never the case in popular structural models (e.g. viewing LRR, habits, heterogeneous agent models etc. as corrections to the C-CAPM), and not at all what GJT find (for consumption models at least)... and cannot correct spurious factors with orthogonal additions.

# Suggestions

- I. needs clear product differentiation – verbatim identical theorems across (not cited) different papers ain't cool.
- II. too much time dedicated to known results – focus on what is new!  
How to estimate the “extended APT” is non-trivial, and worth a paper.
- III. The case of missing factors orthogonal to the observed ones is uninteresting – focus on the relevant case.
- IV. The constraint  $a'\Sigma^{-1}a \leq \delta < \infty$  is crucial – de facto, that's what delivers the identification. For too low  $\delta$  you are imposing perfect pricing for any  $T$  (everything is latent factors). How to chose  $\delta$ ? Cross-validation? Shanken and Barillas (2018 JF)? Sub-sampling in  $N$ ?
- V. Need a clearer case to support the approach. The critique of HJ1, HJ2 etc. based on  $N^2$  dimensionality is a red herring since, in the current estimation procedure, you have the same problem...
- VI. Do asset pricing out-of-sample to show validity of the method... but that's a function of  $\hat{\Sigma}^{-1}$ ...
- VII. Ideally, we should learn from the data something about the behavior of the true SDF – use your method to dig!

## In summary

- (+) The paper is after an important question
- (+) Worth writing an empirical “how to” paper about the “extended APT” (or merge papers?)
- (+) Large  $N$  property is very good (but typo in Theorems or Lemmata?)... use it for estimation!
  
- (-) currently, it takes quite some effort to find what is new
- (-) the dimensionality argument in favor of the approach is, at this stage, misleading
- (-) Needs a criterion for choosing  $\delta$
  
- (=) an interesting paper, with a lot of upside potential  $\Rightarrow$  looking forward to the next draft!

**Note:** it could all be presented in a much simpler fashion: start from the “magic”  $\Sigma^{-1}\alpha$  portfolio, cite the “extended APT” as a way of putting economic restrictions on it, and write a clear “how to” paper with a salient empirical application.