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The Role of Conditioning Information in
Deducing Testable Restrictions Implied by
Dynamic Asset Pricing Models

Econometrica, 55, 1987

Also based on Cochrane Chapter 5

BIG PICTURE RESULTS

EXISTENCE OF SDF

Law of one price

If two portfolios have same payoffs in all states of nature then they must have the same price

$\exists m : p = E m x$ iff law holds

Absence of arbitrage

No arbitrage opportunities

Iff : $\exists m > 0$ $p = E m x$

Back to the basic questions

Instead of starting from general equilibrium consumption - based asset pricing model.

Let us view discount factor as stochastic process satisfying

$$p = E m x$$

- Does there always exist such an m ?
- What markets structure supports this fundamental equation?

- Many aspects of payoff space can be conveniently captured by restrictions on the discount factor.
- Check and impose restrictions on discount factor is easier than on all possible portfolios priced by discount factor.

CONTINGENT CLAIMS

- Suppose S states of nature tomorrow
- Contingent claim pays \$1 (1 unit of consumption)
- $pc(s)$: price today of contingent claim state “s”

COMPLETE MARKET

- Any contingent claim can be bought
- Note that each contract does not have to be traded explicitly
- It can be spanned by other securities (so called synthesized securities e.g. European options with every possible strike)

If a complete set of contingent claims exists, then a discount factor exists and it is equal to the contingent claim prices divided by state probabilities

Let $x(s)$ denote Payoff $\Rightarrow p(x) = \sum_s pc(s) x(s)$

$$p(x) = \sum_s \pi(s) \left[\frac{pc(s)}{\pi(s)} \right] x(s)$$

Where $\pi(s)$ is probability of states

$$m(s) = \frac{pc(s)}{\pi(s)}$$

Then $p = \sum_s \pi(s) m(s) x(s) = E m x$

Therefore in complete markets the stochastic discount factor m exists with $p = E(mx)$

$m(s)$ is state price $pc(s)$ rescaled by probability of state, therefore $m(s)$: State Price Density

Risk neutral probabilities

$$\pi^*(s) \equiv R^f m(s)\pi(s) = R^f pc(s) = \frac{pc(s)}{E(m)}$$

$$\text{and } p(x) = \frac{E^*(x)}{R^f}$$

- Asset pricing becomes as if there is risk neutrality with re-scaled probabilities π^*
- Deep issue : risk aversion is equivalent to paying more attention to certain (unpleasant) states

$$\pi^*(s) > \pi(s)$$

In “bad” states high subjective probabilities

$$\pi^*(s) = \frac{m(s)}{E(m)} \pi(s)$$

- In incomplete markets there are many m , but one is positive
- $m > 0$ but is not unique
- When m is not unique there might be some negative discount factors.

Hilbert Spaces

A non-empty set H is called a Hilbert space if H is a real linear vector space, together with a real-valued function $\langle \cdot, \cdot \rangle$ from $H \times H$ into \mathbb{C} having the following properties:

- $\langle x, x \rangle$ is nonnegative and $\langle x, x \rangle = 0$ iff $x = 0$
- $\langle x+y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$ for all x, y, z
- $\langle ax, y \rangle = a\langle x, y \rangle$ for all x, y in H and a real-valued
- $\langle x, y \rangle = \langle y, x \rangle$ for all x, y in H
- If $\{x_n\}$ is a sequence in H with $\lim_{n, m \rightarrow \infty} \langle x_n - x_m, x_n - x_m \rangle = 0$ then there is an element x in H such that $\lim_{n \rightarrow \infty} \langle x_n - x, x_n - x \rangle = 0$.

Inner product and norm

- The function $\langle \cdot, \cdot \rangle$ is called the inner product
- The real-valued function $\|x\| = \langle x, x \rangle^{1/2}$ is called the norm.
- Schwartz inequality $|\langle x, y \rangle| \leq \|x\| \|y\|$
- Two points x and y in a Hilbert space are orthogonal if $\langle x, y \rangle = 0$
- Riesz representation theorem: for every bounded linear functional x^* on H there is a unique z in H such that $x^*(x) = \langle x, z \rangle$ for all x in H and $\|x^*\| = \|z\|$

Notations:

G_t - all the info at time t

I_t - all the random variables with outcomes in G_t (i.e. measurable functions)

P_{t+1} - all payoffs p_{t+1} on assets at time $t + 1$

$\pi_t(p_{t+1}): P_{t+1} \rightarrow I_t$ price of p at time t

w_t in I_t : portfolio weights

$$p_1, p_2 \text{ in } P \rightarrow w_1 p_1 + w_2 p_2 \text{ in } P$$

Objectives

- Construct a general asset pricing function
- This construction will allow for a very nice decomposition of any return into a sum of three orthogonal components
- The decomposition yields an easy solution to the mean-variance problem
- Discuss conditional vs.unconditional approach
- Bridge to empirical work

One-period setting

- One period setting suffices because of stationarity
- For any p in I_1 consider $P^+ = \{p \in I_1 : E[p^2 | G] < \infty\}$
- Conditional counterpart of inner product on P^+ for any p_a and p_b in P^+ $\langle p_a, p_b \rangle_G = E[p_a p_b | G]$
- We introduce a subset P of P^+ that is restricted to satisfy conditional counterparts of linearity and completeness (i.e. linear combinations of elements of P belong to P and conditional Cauchy sequences converge in P)

Technical (and Economic) Assumptions

Assumption A.1 (Law of one price)

For any p_1, p_2 in P and w_1, w_2 in I

$$\pi(w_1 p_1 + w_2 p_2) = w_1 \pi(p_1) + w_2 \pi(p_2)$$

Assumption A.2 For any $p \geq 0$, $\pi(p) \geq 0$

Assumption A.3 $\exists p_o: \Pr\{\pi(p_o) = 0\} = 0$

Technical Assumption

Implications

The conditional version of the Riesz representation theorem allows us to write $\pi(p) = E(pp^*|G)$ for some $p^* > 0$ with $Pr = 1$.

Moreover, we have that

$$\begin{aligned} \text{A.1: } \quad \pi(w_1 p_1 + w_2 p_2) &= E((w_1 p_1 + w_2 p_2) p^* | G) \\ &= E(w_1 p_1 p^* | G) + E(w_2 p_2 p^* | G) \\ &= w_1 \pi(p_1) + w_2 \pi(p_2) \end{aligned}$$

$$\text{A.2: } \quad p \geq 0 \quad \pi(p) = E(pp^* | G) \geq 0$$

$$\text{A.3: } \quad p_o = 1 \quad \pi(p_o) = E(p^* | G) > 0$$

Theorem

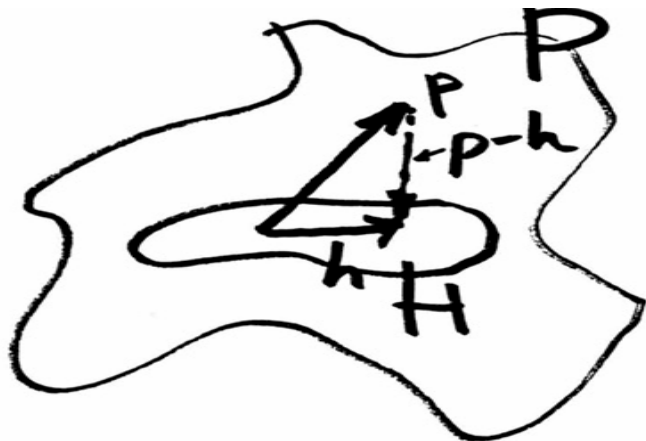
A.1-3 + conditional Riesz theorem are satisfied \Rightarrow
exists unique p^* in P :

$$\pi(p) = E(pp^* | G) = \langle p, p^* \rangle_G \text{ for all } p \text{ in } P$$

$$\Pr \{ \pi(p^*) = 0 \} = 0$$

i.e. ALL pricing functions have such a representation

Lemma (Conditional Projection Theorem)



Find h_0 that minimizes

$$\|p - h\|_G$$

h_0 is unique iff

$p - h_0$ is orthogonal to H

$$\text{i.e. } E((p-h_0) h | G) = 0$$

call h_0 is the projection of p onto H

Sketch of the proof:

Take p_0 that satisfies A.3

z_0 is the projection of p_0 onto Z the conditionally complete linear subspace of P satisfying $\{p \text{ in } P: \pi(p) = 0\}$ and hence $\pi(z_0) = 0$.

$$r^b := \frac{p_0 - z_0}{\pi(p_0 - z_0)} = \frac{p_0 - z_0}{\pi(p_0)} \Rightarrow r^b \text{ orthogonal to } Z$$

Note that $\pi(r^b) = 1$ and r^b is called the benchmark return and r^b is conditionally orthogonal to Z . Note also that:

$$p - \pi(p) r^b \in Z: \pi(p - \pi(p)r^b) = \pi(p) - \pi(p) \pi(r^b) = 0$$

Since $\mathbf{p} - \pi(\mathbf{p}) \mathbf{r}^b \in \mathbf{Z}$

$$\Rightarrow E([\mathbf{p} - \pi(\mathbf{p})\mathbf{r}^b] \mathbf{r}^b | \mathbf{G}) = \langle \mathbf{p} - \pi(\mathbf{p})\mathbf{r}^b, \mathbf{r}^b \rangle_{\mathbf{G}} = 0$$

and therefore

$$E(\mathbf{p}\mathbf{r}^b | \mathbf{G}) = \langle \mathbf{p}, \mathbf{r}^b \rangle_{\mathbf{G}} = \pi(\mathbf{p}) \|\mathbf{r}^b\|_{\mathbf{G}}^2$$

moreover, the technical assumptions imply that $\Pr\{\|\mathbf{r}^b\|_{\mathbf{G}} = 0\} = 0$

$$\pi(\mathbf{p}) = E \left(\mathbf{p} \frac{\mathbf{r}^b}{\|\mathbf{r}^b\|_{\mathbf{G}}^2} \mid \mathbf{G} \right)$$

$\mathbf{p}^* \uparrow$

Definition:

π has no arbitrage opportunities if for any $p \in P$

$$\Pr \{p \geq 0\} = 1 \qquad \Pr(\{\pi(p) \leq 0\} \cap \{p > 0\}) = 0$$

Lemma: π has no arbitrage iff

$$\Pr \{p^* > 0\} = 1$$

$$r^* := \frac{p^*}{\pi(p^*)} \quad - \text{ return on } p^*$$

There are three sets that are of special interest:

$R = \{p \text{ in } P: \pi(p) = 1\}$ space of returns with price 1

$Z = \{p \text{ in } P: \pi(p) = 0\}$ space of returns with price 0

$N = \{z \text{ in } Z: E[z|G] = 0\}$ space of idiosyncratic risk

We will show that

$$R = \{r : r = r^* + wz^* + n\}$$

Where $r^* = p^* / \pi(p^*)$ is return on benchmark asset, projection of stochastic discount factor onto space of assets.

$(wz^* + n)$ is in Z and n is in N

Lemma: (P, π) satisfies A.1-3 + technical assumptions

- (i) $E(r^* z | G) = 0$
- (ii) $\|r^*\|_G \leq \|r\|_G, r \in R$



$$R = \{r : r = r^* + z\}$$

Some implications of results obtained so far:

1. $\|r^*\|_G \leq \|r\|_G$, $r \in R$ implies that r^* conditional minimum mean-variance portfolio (more on this later)
2. When Z is non-empty asset pricing does not coincide with risk neutral pricing

Problem C $\min \|r\|_G^2$

$$\text{s.t. } E(r|G) = w \in I$$

$$w^* = \frac{w - E(r^*|G)}{E(z^*|G)}$$

$$E(r|G) = w \Leftrightarrow r = r^* + w^*z^* + n$$

$\Rightarrow n = 0$ solves the problem

What is the effect of omitting the info?

Consider R^*, Z^*, N^*

$$R^* = \{r : r = r^* + cz^* + n^*\}$$

Problem U $\min \|r\|^2$
s.t. $E(r) = c$

$$c^* = [c - E(r^*)] / E(z^*)$$

$$E(r) = c \Leftrightarrow r = r^* + c^* z^* + n^*$$

$n^* = 0$ solves the problem

Back to Big Picture

Want to test $H_0 : r_i$ is on the frontier

Method: Test CAPM via regression

However, when we do not take into account conditioning information Hansen and Richard show that rejection of CAPM does not necessarily mean that a portfolio is not mean-variance efficient.

Conditional vs unconditional factor models in discount factor language

Consider CAPM

$$r^* = m^* = a - bR^W$$

Where R^W is the return on the market or wealth portfolio

$$1 = E_t m_{t+1}^* R_{t+1}^W$$

$$1 = E_t m_{t+1}^* R_{t+1}^f$$

We can solve for a and b

$$a = \frac{1}{R_t^f} + bE_t(R_{t+1}^W)$$

$$b = (E_t(R_{t+1}^W) - R_t^f) / R_t^f \sigma_t^2(R_{t+1}^W)$$

But this means a and b vary over time

If it is to price assets conditionally, the CAPM model must be linear factor model with time-varying weights:

$$m_{t+1}^* = a_t + b_t R_{t+1}^W$$

Therefore

$$1 = E_t[(a_t + b_t R_{t+1}^W) R_{t+1}]$$

While we can say:

$$1 = E[(a_t + b_t R_{t+1}^W) R_{t+1}]$$

We cannot say

$$1 = E[(a + bR_{t+1}^W)R_{t+1}]$$

Instead:

$$\begin{aligned} 1 &= E(a_t)E(R_{t+1}) + E(b_t)ER_{t+1}^W R_t \\ &+ Cov(a_t, R_{t+1}) \\ &+ Cov(b_t, R_{t+1}^W R_{t+1}) \end{aligned}$$

Only when the covariances are zero then,

$$1 = E[E(a_t) + E(b_t)R_{t+1}^W]R_{t+1}]$$

In general

$$\text{Cov}\left(\frac{1}{R_t^f} + b_t E_t(R_{t+1}^W), R_{t+1}\right) \neq 0$$

$$\text{Cov}\left(\frac{E_t(R_{t+1}^W) - R_t^f}{R_t^f \sigma_t^2(R_{t+1}^W)}, R_{t+1} R_{t+1}^W\right) \neq 0$$

Of course if:

$$a_t = a, b_t = b$$

Then,

$$1 = E(a + bR_{t+1}^W)R_{t+1}$$

CONDITIONAL VS UNCONDITIONAL IN AN EXPECTED RETURN/BETA MODEL

$$E_t(R^i) = R_t^f + \beta_t \lambda_t$$

Does not imply

$$E(R^i) = \alpha + \beta \lambda$$

If returns & factors are i.i.d. then $\text{Cov}(.) = \text{Cov}_t(.), \text{Var}(.) = \text{Var}_t(.)$

So that,

$$\beta_t = \beta$$