

Empirical Finance Lecture 2: Tests of the EMH

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Last time...

- Price/return series (e.g., FTSE 250,) are not well modelled with the RWM:
 - Prices are non-stationary but...
 - **Returns** are *not* independent:
 - \blacksquare Volatility clustering \Rightarrow non-linear dependence.
 - **Example 1** Are they linearly independent? (today's topic).
 - Returns are (very) non-Gaussian.

Today...

- A less restrictive version of the RWM.
 - The martingale model (MM).
- E Tests of return predictability.
 - ACFs
 - **Regression** based tests
 - Variance ratio tests
- The interpretation of evidence for return predictability.
 - E Critical appraisal of the relationship between the RWM/MM and EMH.

Martingale Model

- Example: There are 2 main objections to the RWM as a DGP for financial data:
 - E Assumption of independence of returns.
 - E Assumption of normality of returns.
- The MM is similar to the RWM but assumes only that returns are linearly independent.
- The MM therefore provides a better description of price movements under the EMH.

Martingale model (Cuthbertson and Nitzsche 3.3)

 $\{x_t\}$ is a martingale process if:

i) $E(|x_t|) < \infty$ (the mean is bounded) ii) $E(x_{t+h}|\Omega_t) = x_t, h > 0$ Martingale property

A martingale is a model of a fair game

$$E(x_{t+h} - x_t | \Omega_t) = 0$$

The process is a sub-martingale if $E(x_{t+h} - x_t | \Omega_t) > 0$ It is a super-martingale if $E(x_{t+h} - x_t | \Omega_t) < 0$ The expected h-period return is zero.

Example of a fair game: A game of tossing an unbiased coin:

win £1 for a head; lose £1 for a tail

The expected return is £0 per play:

E(r)=1×0.5 -1 ×0.5=0

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Martingale model

We can write an equation for x which looks rather like the RWM:

$$x_t = x_{t-1} + \mathcal{E}_t$$
If the process is a sub- or super- martingale then
Include a drift term in the equation
$$x_t = \mu + x_{t-1} + \mathcal{E}_t$$

where ε is a martingale difference (or increment).

The fair game property means that the best guess of a future increment is that it equals zero.

$$E\left(\varepsilon_{t+h} \middle| \Omega_t\right) = 0, \quad h > 0$$

However there is no assumption that the increments are

1. Independent (fair game property \Rightarrow linear independence only).

2. Normally distributed.

Indeed neither independence nor a Gaussian distribution is required for returns under the EMH (only linear independence).

MM and the EMH (Cuthbertson & Nitzsche 3.1-3.4)

- EMH states that asset prices fully reflect all available relevant information:
- The only systematic/predictable gain (change in price) is the required rate of return on the asset. Other gains/losses are attributable to unpredictable events: news

 \implies \Rightarrow Investors cannot make abnormal profits systematically from buying and selling assets: <u>risk adjusted returns are a fair game</u>

Investors form rational expectations: i) They know Ω_t and the true model for returns; and ii) They use this information to predict future returns

$$E(r_{t+1}|\Omega_t) - \mu = E(\mathcal{E}_{t+1}|\Omega_t) = 0$$
RE implies forecast errors are unpredictable given Ω_t

The key empirical prediction of the MM/EMH is that future returns are <u>linearly</u> independent from information available in the current or previous periods.

Empirical testing of EMH

EMH comes in 3 flavours depending on what constitutes the relevant information set:

- 1. Weak form efficiency current price incorporates all the information on past prices.
- 2. Semi strong efficiency current price incorporates *all* publicly available information.
- 3. Strong form efficiency– current price incorporates *all* information including insider information.
- Tests of EMH are usually of the weak or semi-strong form variety.

Tests of weak/semi-strong form EMH (Brooks 5.2)

III Analysis of the ACF of returns

Implied by linear independence

$$cov(r_t, r_{t-s}) = 0, \ s > 0$$

$$\Rightarrow \rho_s = \frac{cov(r_t, r_{t-s})}{var(r_t)} = 1, \ s = 0$$

$$= 0, \ s > 0$$

The population ACF of a linearly independent process is flat at zero for all positive lags.

Risk adjusted returns have exactly the same ACF as here (assuming constant equilibrium returns).

A mean zero, linearly independent process (such as risk adjusted returns) is a WHITE NOISE process.

White noise has an ACF with the shape given here.

In any given sample $\hat{\rho}_s \neq 0$ even if $\rho_s = 0$ If $\rho_s = 0$ The null hypothesis...

$$H_0: \rho_1 = \rho_2 = ... = \rho_k = 0$$

with the Ljung-Box Q statistic

('portmanteau' statistic):

$$Q(k) = T(T+2)\sum_{i=1}^{k} (T-i)^{-1} \hat{\rho}_{i}^{2} \sim \chi_{k}^{2}$$

...can be tested

ACFs of return series

FTSE 250 returns UK-US exchange rate returns

Date: 01/1		: 13:58							1/07 Time					
-	2/31/1985 1								974M01 20					
Included observations: 5051								Included o	bservations	: 386				
Autocorrel	Partial Cor	Lag	AC	PAC	Q-Stat	Prob		Autocorrel	Partial Cor	Lag	AC	PAC	Q-Stat	Prob
**	**	1	0.216	0.216	236.19		0	1	0.062	0.062	1.4991	0.22
*	*	2	0.11	0.067	297.75		0	2	0.008	0.005	1.527	0.46
*		3	0.078	0.044	328.66		0	3	-0.002	-0.003	1.5284	0.67
*	*	4	0.124	0.098	407.01		0	4	0.018	0.018	1.6532	0.79
		5	0.051	-0.002	420.02		0	5	0.026	0.024	1.9126	0.86
		6	0.016	-0.013	421.36		0	* .	* .	6	-0.063	-0.067	3.4875	0.74
		7	0.06	0.049	439.51		0	7	0	0.008	3.4875	0.83
*		8	0.076	0.045	468.85		0	8	0.016	0.017	3.5922	0.89
*		9	0.077	0.045	498.53		0	. *	. *	9	0.071	0.068	5.5848	0.78
		10	0.045	0.011	508.62		0	10	-0.041	-0.049	6.2627	0.79
*		11	0.069	0.038	532.45		0	. *	. *	11	0.118	0.128	11.791	0.3
		12	0.026	-0.016	535.96		0	12	-0.004	-0.026	11.798	0.46
		13	0.001	-0.024	535.96		0	13	0.027	0.026	12.085	0.52
		14	0.02	0.014	538		0	* .	* .	14	-0.137	-0.147	19.659	0.14
		15	0.029	0.011	542.22		0	* .	. .	15	-0.075	-0.047	21.908	0.1
•														
	Linear independence/EMH rejected					ed		Linear	indepe	endence	e/EMH	cannot	be reje	ected

Tests of semi-strong EMH (Cuthbertson & Nitzsche 4.2-4.3)

<u>Regression tests of return predictability:</u>

$$r_{t+1} = \mu + \beta' \Omega_t + u_{t+1}$$

If excess returns are a fair game, $E_t(r_{t+1}) - \mu = 0$, then the elements of the $k \ge 1$ vector of coefficients β are jointly zero.

A test of EMH is therefore:

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0 \text{ versus}$$
$$H_1: \text{At least one of the } \beta' s \neq 0.$$

This can be tested using an *F*-test (see Gujarati Chp 8/ Brooks Chp 3):

$$F = \frac{ESS / k}{RSS / [T - (k+1)]} \sim F_{k,T-(k+1)} \text{ under } H_0.$$

Regression tests of return predictability

What variables are included in Ω ?

- 1. Data on past returns (another test of 'weak form' efficiency).
- 2. Data on past news \mathcal{E}_{t-j} , $j \ge 0$: Autoregressive moving average models.
- 3. Data on other financial variables such as dividend yields, E/P and interest rates (see Fama, 1991, for a discussion).
- Data related to various 'anomalies' (e.g., small firm and calendar effects: see Cuthbertson & Nitzsche 18.4).

A fifth order autoregression with calendar effects for FTSE250 returns

					$\hat{r}_t = \hat{\mu} + \hat{\beta}_1 MONDAY + \hat{\beta}_2 JANUARY$
Dependent	Variable: F	TSE_250_	RETURNS		
Method: Least Squares					$+\hat{\beta}_{3}r_{t-1}+\hat{\beta}_{4}r_{t-2}+\hat{\beta}_{5}r_{t-3}+\hat{\beta}_{6}r_{t-4}+\hat{\beta}_{7}r_{t-5}$
					$r^{2} 3^{+} t^{-1} r^{2} 4^{+} t^{-2} r^{2} 5^{+} t^{-3} r^{2} 6^{+} t^{-4} r^{2} r^{-1} t^{-5}$
• •	djusted): 1/				
			adjustmen	ts	
Convergen	ce achieved	l after 5 iter	rations		
				_ ·	
Variable	Coefficient	Std. Error	t-Statistic	Prob.	MONDAY=1 if DoW is Monday
0	0.000544	0.00010	0.004500	0.0007	=0 otherwise
С	0.000541	0.00018		0.0027	JANUARY=1 if Month is January
MONDAY	-0.00051	0.000249		0.0409	=0 otherwise
JANUARY				0.2204	
AR(1)	0.1948			0	Coefficients on
AR(2)	0.052071	0.014286			
AR(3)	0.023881	0.014304		0.0951	$r_{t-1},, r_{t-5}$
AR(4)	0.098634				
AR(5)	-0.00293	0.014096	-0.20787	0.8353	
R-squared 0.063025 Mean depend		ependent va	0.000503		
Adjusted F			pendent var		
S.E. of reg	.E. of reg 0.007552 Akaike info criterio		-6.9324		
•	0.287338		z criterion	-6.92205	Semi-strong EMH rejected
•	17498.45	F-statistic		48.41123	for FTSE250 returns
Durbin-Wa	1.99968	Prob(F-	statistic)	0	

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Interpreting these results

- These results indicate a violation of informational efficiency for the FTSE250.
 - For example, a trading strategy of short-selling the index on Friday and repurchasing on Monday yields a predictable return of 0.05%
- However this need not imply that investors can derive persistent abnormal profits in the 'real world':
- I. Buying/selling shares incurs transactions costs.
 - Transactions costs of 5p per £100 traded would wipe out profits from the above trading strategy.
 - A flat rate fee of £10 per trade (competitive against e.g., TD Waterhouse) would require a transaction larger than £20K to start making a profit. This is risky! (see below)
- **2.** Low R^2 implies potential arbitrage opportunities are very <u>risky</u>:
 - Only 6% of the total variation in returns is explained by the model.
 - Actual returns could be much higher or lower than expected.
- **3.** The relationship may be unstable over time
 - Test the model for parameter stability before betting your house/career on your trading strategy.

Short vs long horizon returns

Positive autocorrelations in the short run may be due to <u>noise traders</u> These traders (irrationally) interpret random price changes as containing information which can be used to forecast future changes.

- A <u>positive feedback trader</u> is a noise trader who believes that a random price rise today is indicative of a price rise tomorrow.
- The <u>smart money</u>, on the other hand, knows that price movements are random and are useless for forecasting.
- Following a price rise positive feedback traders bid up the price of the stock yet further driving the price further away from fundamentals (equilibrium level)
 - \Rightarrow <u>positive</u> autocorrelation over short horizons (e.g., <1 year).

Eventually though the bubble bursts:

Prices/returns go back to their equilibrium level:

mean reversion.

 \Rightarrow <u>negative</u> autocorrelation over longer horizons (e.g., 1 year or more).

Variance ratio tests

These tests are widely used to test for mean reversion.

They involve comparisons of return variances for different <u>holding periods.</u>

k-period holding returns are given by:

$$r_{t,t+k} = \ln P_{t+k} - \ln P_t = k\mu + \varepsilon_{t+1} + \varepsilon_{t+2} + \dots + \varepsilon_{t+k}$$

$$E(r_{t,t+k} | \Omega_t) = k\mu,$$

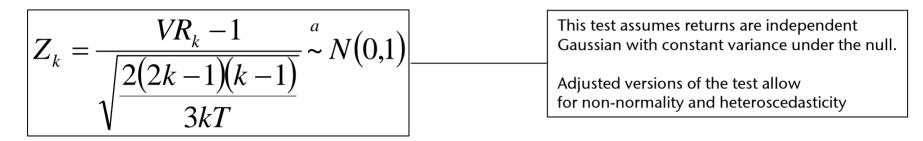
$$var(r_{t,t+k}) = k\sigma^2$$
Assuming returns are linearly independent with constant variance then risk and return Increase with the holding period.
$$If returns are linearly independent then VR_k = 1 at all horizons.$$
Mean aversion \Rightarrow positive autocorrelation in returns $\Rightarrow VR_k > 1$
Mean reversion \Rightarrow negative autocorrelation in returns $\Rightarrow VR_k < 1$

Poterba and Summers (1988) found US stock returns displayed mean aversion for k<1year and mean reversion for k>1 year

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Variance ratio tests

III A test for $H_0: VR_k = 1$ is given by (see Cuthbertson & Nitzsche 4.3):



WR test results for FTSE250 returns:

k	50 days	100 days	200 days	500 days
VR_k	2.590	2.439	2.096	1.539
$Z_k(p-value)$	0.000	0.000	0.000	0.138

There is substantial <u>mean aversion</u> for horizons of under a year.

There is <u>no</u> evidence for mean reversion at any horizon: returns move away from equilibrium and never return.

Other interpretations of the results (when is a correlation not evidence against the EMH?)

It's possible that return predictability is not a symptom of market inefficiency at all! Instead, it may be a symptom of:

1. A poor model of equilibrium returns

Or a market microstructure issue e.g.,

- 2. Bid/ask bounce
- 3. Infrequent or non-synchronous trading

1. A poor model of equilibrium returns

Only able to test EMH conditional on a specific model of equilibrium returns (so far we have simply assumed μ is a constant – no structure)

There is a 'joint hypothesis problem'

'As a result, when we find anomalous evidence on the behavior of returns, the way it should be split between market inefficiency or a bad model of market equilibrium is ambiguous.' Fama (1991) p 1576 Even possible for returns to be predictable even when

markets are informationally efficient! (Leroy, 1973)

(MM⇔EMH only under risk neutrality)

Illustration of joint hypothesis problem

Suppose the true model of returns is

$$r_{t+1} = r_f + \lambda \sigma_{t+1}^2 + \varepsilon_{t+1}$$

where ε is a martingale difference. <u>Volatility clustering</u> (see lecture 1) implies risk is time-varying and predictable. This equation follows by applying CAPM to the market portfolio

$$E(r) - r_{f} = \beta \left[E(r_{m}) - r_{f} \right]$$

$$= \frac{\operatorname{cov}(r, r_{m})}{\sigma_{m}^{2}} \left[E(r_{m}) - r_{f} \right]$$

$$= \lambda \operatorname{cov}(r, r_{m})$$

$$= \lambda \sigma_{m}^{2}, \quad r \equiv r_{m}$$

$$\lambda \text{ Is the MARKET PRICE OF RISK :}$$

$$\left(E(r_{m}) - r_{f} \right) / \sigma_{m}^{2}$$

The GARCH(1,1) model is commonly used in finance to model volatility clustering

Conditional variance
$$\sigma_{t+1}^2 = \delta + \alpha \sigma_t^2 + \beta \varepsilon_t^2$$

Illustration of joint hypothesis problem

The CAPM model plus GARCH means r_{t+1} is predictable because:

i) investors are risk averse (λ >0).

ii) risk today is a predictor of risk tomorrow (volatility clustering).

But, conditional on investors' preferences, price movements are unpredictable (i.e., the ε satisfy the EMH).

Illustration of joint hypothesis problem

If we mistakenly assumed (log) prices followed a (sub) martingale model (MM)

$$r_{t+1} = \mu + \mathcal{E}_{t+1}$$

then it would appear that EMH is violated because we have not taken into account:

i) risk aversion

ii) volatility clustering.

As a consequence, the time varying risk premium is subsumed in ϵ so that returns are predictable.

But the problem is a poor model of equilibrium returns rather than violation of EMH

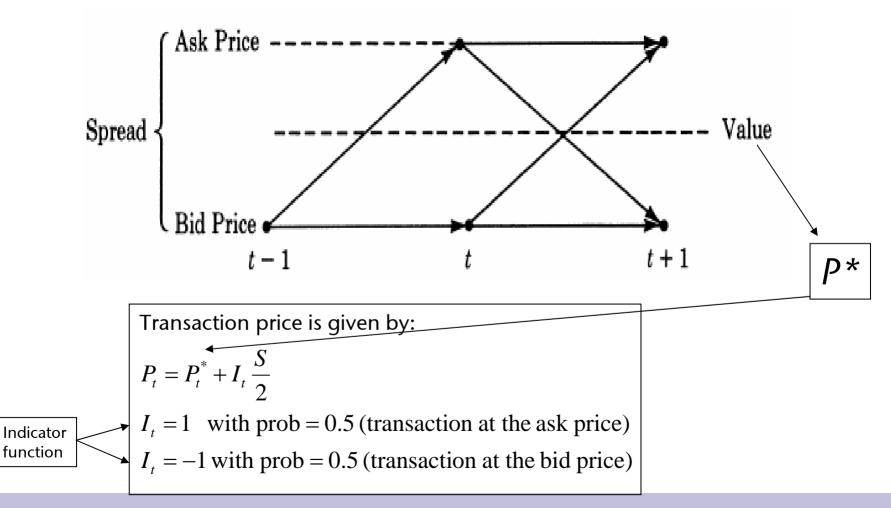
Note that if investors are risk neutral (λ =0) then MM \Leftrightarrow EMH.

2. Bid-ask bounce

Market makers:

- Buy stocks from the public at a *bid* price P_b
- Sell stocks to the public at an *ask* price P_a
- The bid-ask spread $S \equiv P_a P_b$ reflects order processing costs, inventory costs and adverse selection costs
- Recorded transactions could be at either the bid or ask price.
- This gives rise to spurious negative autocorrelation in returns as a result of the recorded transaction 'bouncing' between the bid and ask price (see next slide).

2. Bid-ask bounce



2. Bid-ask bounce causes spurious negative autocorrelation in price movements

- III To show this need to derive the mean, variance and first order covariance of ΔI_{t}
- III Firstly the probability distribution of ΔI_t is:

Ask to bid :
$$\Delta I_t = 1 - 1 = 2$$
 with prob = 0.25
Ask to ask : $\Delta I_t = 1 - 1 = 0$ with prob = 0.25
Bid to ask : $\Delta I_t = -1 - 1 = -2$ with prob = 0.25
Bid to bid : $\Delta I_t = -1 - -1 = 0$ with prob = 0.25
 $E(\Delta I_t) = 2 \times 0.25 - 2 \times 0.25 = 0$
 $vat(\Delta I_t) = E(\Delta I_t^2) = 4 \times 0.25 + 4 \times 0.25 = 2$
 $cov(\Delta I_t, \Delta I_{t-1}) = E(\Delta I_t \Delta I_{t-1}) = -E(I_{t-1}^2) = -1$
 $E(I_{t-1}) = I \times 0.5 + 1 \times 0.5 = 1$

2. Bid-ask bounce causes spurious negative autocorrelation in price movements

Assume the underlying share value P_t^* follows a martingale

$$\Delta P_t^* = \varepsilon_t$$
Then the observed price changes are:
$$\Delta P_t = \varepsilon_t + \Delta I_t \frac{S}{2}$$

$$E(\Delta P_t) = E(\varepsilon_t) + E(\Delta I_t) \frac{S}{2} = 0$$

$$var(\Delta P_t) = var(\varepsilon_t) + var(\Delta I_t) \frac{S^2}{4} = \sigma^2 + \frac{S^2}{2}$$

$$cov(\Delta P_t, \Delta P_{t-1}) = E(\Delta P_t \Delta P_{t-1})$$

$$= E\left[\left(\varepsilon_t + \Delta I_t \frac{S}{2}\right)\left(\varepsilon_{t-1} + \Delta I_{t-1} \frac{S}{2}\right)\right] = \frac{S^2}{4} E(\Delta I_t \Delta I_{t-1})$$

$$= \frac{-S^2}{4}$$

$$\Rightarrow \rho_1 = \frac{-S^2/4}{\sigma^2 + S^2/2} \le 0$$
Price changes have first order negative autocorrelation even though the change in P* is a fair game.

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3. Infrequent or non-synchronous trading

- Non-trading can lead to spurious *positive* autocorrelation in stock returns.
- Intuition here is that news is incorporated into large caps first and into small caps with a lag/delay (because small caps trade less frequently).
- Yesterday's news is present in both yesterday's and today's return via large caps and small caps respectively.
- Therefore the returns of an equal weighted index (comprised of small and large caps) will be positively correlated.
- Value-weighting can help to mitigate this problem (gives less weight to small caps in the index).

Conclusions

- Information gathering is costly.
- It therefore seems unreasonable to expect the EMH to hold instantly in every period.
 - Successful) careers in investment management rely on better information acquisition or financial innovation to earn abnormal returns for clients.
- The issue then is one of *relative* efficiency (e.g., How big are the abnormal returns from a particular trading strategy versus a passive buy and hold strategy? Are they long-lasted?)
- Example Tendamentally, any test of the EMH is conditional on the assumed DGP for prices/returns (joint hypothesis problem).

References

Brooks (2002), Introductory econometrics for finance, CUP: Cambridge.**

- Cuthbertson and Nitzsche (2004) Quantitative financial economics: stocks, bonds and foreign exchange, Wiley: Chichester.**
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- LeRoy (1973) Risk aversion and the martingale property of stock returns, *International Economic Review*, 14, 436-446.

** Key references