Lecture 9: Market Efficiency, return predictability and portfolio allocation

Investments

Market Efficiency

- **Definition:** *An efficient market is one that incorporates all available information*

  This means that we cannot predict future price paths based on information available today. Prices should adjust immediately to reflect all available information.

  ↪ **Weak Form Efficient**
  Prices incorporate all information contained in past prices.

  ↪ **Semi-Strong Form Efficient**
  Prices incorporate all *public* information.

  ↪ **Strong Form Efficient**
  Prices incorporate all information, public and *private*.

- Paul Samuelson:

  Modern markets show considerable micro-efficiency (for the reason that the minority who spot aberrations from micro efficiency can make money from those occurrences and, in doing so, they tend to wipe out any persistent inefficiencies). In no contradiction to the previous sentence, I had hypothesized considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values.

Stock Prices as Random Walks

- According to the weak-for of the EMH, stock prices should follow random walks.
  - $\hookrightarrow$ In his 1900 dissertation on "The Theory of Speculation", Louis Bachelier searched for a "*formula that expresses the likelihood of a market fluctuation."* He ended up with a mathematical formula that describes the *Brownian Motion*, or *random walk* as it came it called in the finance world.
- Prices as random walks implies that price changes (i.e. returns) should be uncorrelated with past price changes, or equivalently should have *zero autocorrelation*, i.e. $corr(R_t, R_{t-1}) = 0$

Informational Efficiency

- Of course, the "efficiency" of markets may be a relative concept. It is possible that markets are efficient in the long-run, but in the short run it make take some time before information is diffused.
- Grossman and Stiglitz (1980) argue that perfectly efficient markets are an impossibility
  - ↪ Suppose that price incorporates all available information.
  - ↪ If information gathering is costly, no one would be collecting information.
  - ↪ Grossman-Stiglitz paradox: How is then information impounded the prices?
- Nevertheless, one should not be making abnormal returns using only information that is freely available.

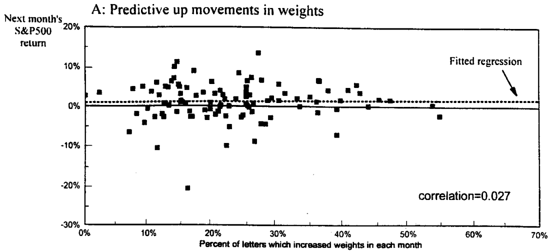
Market efficiency

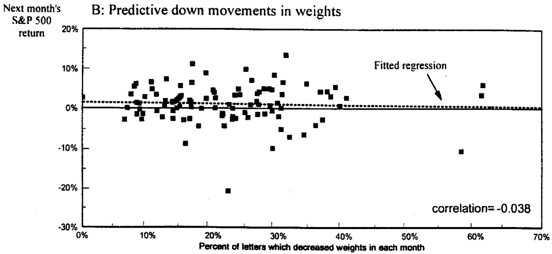
- There are two, apparently conflicting, pieces of evidence:
  1. Analyst recommendations have no ability to predict future market returns.
  2. Past price movements *do* predict future market returns.
- Point 2 suggests that markets may be inefficient. But if this is so, why isn't everyone rich?

Investment analysts and market efficiency

- If markets are efficient, then what is the role of information analysts?
- A large literature has found that analyst forecasts are biased, starting from Mastrapasqua and Bolten (1973) and Brown and Rozeff (1978).
- Analyst forecast are often found to contain no incremental information.
- Graham and Harvey (1996) examined 237 newsletter strategies. They found no evidence that there is information about future returns

Market timing ability of investment managers

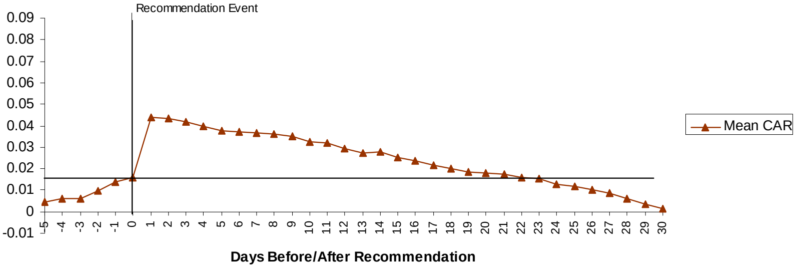




Case Study: Jim Cramer

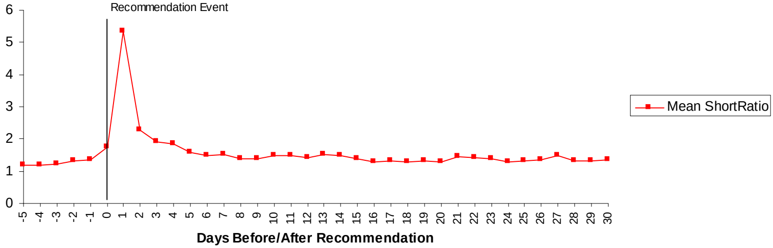
- Do analyst forecast have any effect on prices?
- Example: Can You Make Money From Jim Cramer's Picks?
  - ↪ Jim Cramer is the host of CNBC's Mad Money, with an average viewership of 400,000.
- 3 Kellogg Ph.D. Students asked that question. They looked at 246 recommendations made in July - October 2006.

- Graph shows average deviation of stock price from "fundamental" values.



- Some savvy investors are aware of this and are betting against it!

Figure 4: Mean ShortRatio around Recommendation Event

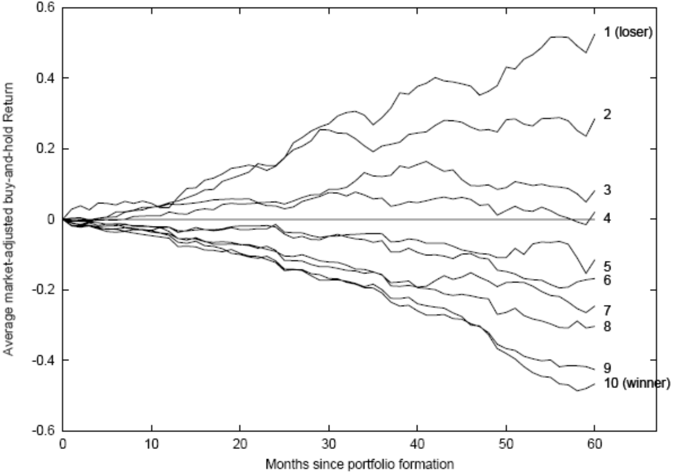


Past prices predict future returns

- Stock prices appear to exhibit *reversals* over longer horizons.
- In a 1985 *Journal of Finance*, De Bondt and Thaler show that over 3- to 5-year holding periods stocks that perform poorly over the previous 3 to 5 years achieve higher returns than stocks that perform well.
- That is, contrarian strategies (buying past losers and selling past winners) achieve abnormal returns.
- They attribute this result to the *overreaction* of the stock markets to information.
- Long-term reversal is just further evidence that stock returns are *predictable*

Long Term Reversal

- Portfolios of stocks sorted on past 5 year returns.



Long Horizon Predictability

- There is small evidence for predictability over short horizons.
- Over long horizons however, the predictability 'adds up'
  - ↪ Over a 3-5 year horizon, R^2 can be as high as 30%!.
- In other words, over long horizons, stock returns are mean-reverting.
  - ↪ This has led many economists to advocate that stocks are less risky in the long run (Remember Lecture 2?)

Long-Horizon Autocorrelations

$$r(t, t+T) = \alpha(T) + \beta(T) r(t-T, t) + \epsilon(t, t+T)$$

	Return Horizon (Years)							
	1	2	3	4	5	6	8	10
	OLS Slopes $\beta(T)$							
Food	−.04	−.28*	−.41*	−.46*	−.47*	−.30	−.21	−.20
Apparel	−.11	−.23	−.27	−.37*	−.43*	−.37	−.43	−.56*
Drugs	−.04	−.19	−.25	−.22	−.26	−.22	−.31	−.50
Retail	−.03	−.22	−.37*	−.42*	−.46*	−.34	−.32	−.31
Durables	.00	−.19	−.34*	−.43*	−.43*	−.25	−.20	−.15
Autos	−.07	−.27	−.43*	−.52*	−.48*	−.29*	−.26	−.30
Construction	−.03	−.17	−.34*	−.51*	−.55*	−.36*	−.06	−.04
Finance	−.04	−.22	−.33*	−.35*	−.28	−.09	.00	.06
Miscellaneous	−.04	−.18	−.32*	−.45*	−.50*	−.34	−.22	−.17
Utilities	−.07	−.21	−.35*	−.32*	−.15	.08	−.08	−.18
Transportation	−.12	−.25	−.34*	−.44*	−.45*	−.33	−.30	−.27
Business equipment	−.01	−.26	−.46*	−.51*	−.49*	−.35*	−.17	−.15
Chemicals	−.06	−.38*	−.50*	−.48*	−.50*	−.34*	−.21	−.17
Metal products	−.02	−.25	−.45*	−.59*	−.65*	−.53*	−.38*	−.33*
Metal industries	−.10	−.32*	−.43*	−.46*	−.48*	−.33*	−.04	−.01
Mining	−.11	−.33*	−.44*	−.54*	−.61*	−.44*	−.20	−.21
Oil	−.04	−.28*	−.36*	−.52*	−.53*	−.36*	−.05	−.01
Average $\beta(T)$	−.06	−.25	−.38	−.45	−.45	−.30	−.20	−.21

Return Predictability

- Does predictability in returns really violate EMH?
  - ↪ One of the implications of the random walk model, is that stock price changes are *unpredictable*. This means that the best forecast of tomorrow's return is the historical average return.
  - ↪ But what if stock β (or systematic risk) changes over time? Is the historical average return the best forecast of past returns?
- Not really! In fact, any variable that is positively correlated with the new β will appear to predict firm-level returns.
- Return predictability is *equivalent* to time varying expected returns

Return Predictability - Example

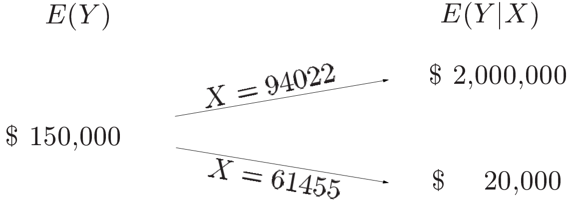
- Suppose the CAPM holds and markets are efficient.
- Company ABC had a historical β of 1.0, the market premium is 6.00%, the risk-free rate is 2%. ABC has zero debt. ABC's expected return is $2\% + 1 \times 6\% = 8\%$
- ABC decides to buy back half its shares and issue debt instead.
  1. ABC went from being 100% equity financed to being 50% equity 50% debt.
  2. ABC's leverage has increased but its asset β hasn't changed.

$$\text{Asset } \beta = 50\% \times \text{Equity } \beta + 50\% \times \text{Debt } \beta$$

  3. Assuming β of debt is zero, new equity $\beta = 2$
- What are the expected returns on ABC going forward?
- Now changes in leverage appear to forecast future stock returns!

Conditional Expectations

- Suppose Y is the price of a single family house and X is the zip code.



- The *conditional expectation*, $E(Y/X)$ is not the same as the *unconditional* expectation $E(Y)$ if X allows us to better forecast Y
  - ↪ $E(Y)$ is a number whereas $E(Y/X)$ is a random variable because it depends on the variable X.
- We can think of X as representing additional information that enables us to better forecast the value of a house.

Conditional Expectations

- Regression is an example of a conditional expectation:

$$Y = \alpha + \beta X + \varepsilon$$

- The unconditional expectation of Y, $E(Y)$, is the historical average of Y.

- The expectation of Y conditional on X:

$$E(Y/X) = \alpha + \beta X$$

  is a random variable because it depends on X.

  - When is $E(Y/X) = E(Y)$?
  - Note that, on average, the conditional expectation has to equal the unconditional, that is $E[E(Y/X)] = E(Y)$.

Return Predictability

- Evidence for return predictability can be interpreted as time-variation in expected returns.

- Predictability in returns implies that

$$E[R_{t+1}|X_t] \neq E[R_{t+1}]$$

  that is, conditional on information available at time t, (X_t), our expectation of the future is different than the long run average or the unconditional expectation.

- Which variables are likely to predict the market?

Dividend Yield and Discount Rates

- If discount rates are time-varying, the dividend yield should partially reveal them.
- Remember the Gordon Growth formula:

$$\frac{D_t}{P_t} = \frac{r-g}{(1+g)}$$

- This is not completely correct since the GG formula is derived under the assumption that dividend growth (g) and expected returns (r) are constant.
- But it provides useful intuition: if discount rates rise, all else equal, price-dividend ratios drop

(4x) Dividend Yield and subsequent 7-Year Stock Returns

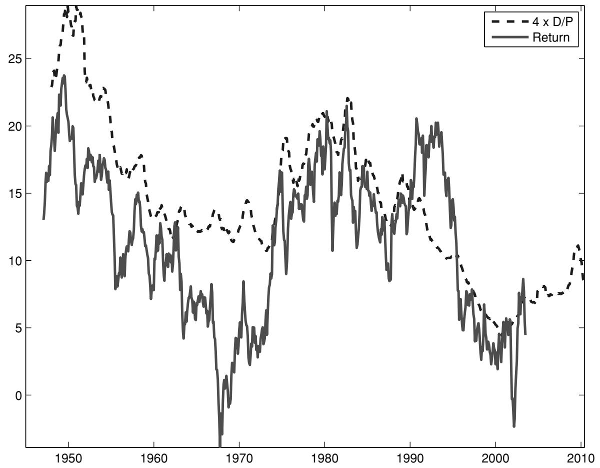


Figure 1. Dividend yield and following 7-year return. The dividend yield is multiplied by four. Both series use the CRSP value-weighted market index.

Forecasting regressions

Regression	b	t	$R^2(\%)$	$\sigma(bx)(\%)$
$R_{t+1} = a + b(D_t/P_t) + \varepsilon_{t+1}$	3.39	2.28	5.8	4.9
$R_{t+1} - R_t^f = a + b(D_t/P_t) + \varepsilon_{t+1}$	3.83	2.61	7.4	5.6
$D_{t+1}/D_t = a + b(D_t/P_t) + \varepsilon_{t+1}$	0.07	0.06	0.0001	0.001
$r_{t+1} = a_r + b_r(d_t - p_t) + \varepsilon^r_{t+1}$	0.097	1.92	4.0	4.0
$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \varepsilon^{dp}_{t+1}$	0.008	0.18	0.00	0.003

R_{t+1} is the real return, deflated by the CPI, D_{t+1}/D_t is real dividend growth, and D_t/P_t is the dividend-price ratio of the CRSP value-weighted portfolio. R^f_{t+1} is the real return on 3-month Treasury-Bills. Small letters are logs of corresponding capital letters. Annual data, 1926–2004. $\sigma(bx)$ gives the standard deviation of the fitted value of the regression.

A Pervasive Phenomenon

This pattern of predictability is pervasive across markets:

- Stocks: Dividend yields forecast returns, not dividend growth.
- Treasuries: A rising yield curve signals better 1-year returns for long-term bonds, not higher future interest rates.
- Corporate Bonds: Much variation in credit spreads over time and across firms predicts returns, not default probabilities.
- Foreign exchange: International interest rate spreads predict returns, not exchange rate depreciation.

Reasons for predictability

Predictability of **market returns** can arise for two reasons

1. In an *inefficient* market, predictability can arise because investors do not properly incorporate all available information. In this case past prices and public information can help forecast future stock returns as investors correct their mistakes.
2. In an *efficient* market, predictability can arise because the expected reward for holding the market portfolio is time varying. This can happen because
   a) The *risk* or volatility of the market portfolio varies over time, and so does the investor's reward for bearing that risk.
   b) Investor's attitudes towards *risk* may change. For example during recessions, investors may become more risk averse and therefore demand a higher premium in order to hold the market portfolio.

Return predictability

- Why do discount rates change over time? Go back to the formula describing the optimal allocation to one risk asset (the market portfolio) and the risk-free asset

$$w^* = \frac{E(R_M) - r_f}{A\sigma_M^2}$$

  - $\hookrightarrow$ In equilibrium $w^* = 1$, i.e. riskless borrowing and lending cancel out
  - $\hookrightarrow$ What happens if risk (σ_M), or risk aversion A increase?
  - $\hookrightarrow$ Discount rates need to rise $\rightarrow$ prices need to drop today

- In the data, only weak evidence that σ_M predicts returns.

- All the action must come from "risk aversion". A metaphor for many things: investor fear of uncertainty, capital constraints, sentiment

Market Timing

- If market returns are predictable, then we can 'time' the market.
  - $\hookrightarrow$ You may be using variables like the dividend yield, business cycle indicators or macroeconomic analysis to forecast returns.
- In order to exploit this, you can shift funds between a market index portfolio and a safe asset based on your forecasts:

$$\tilde{r}_p = w_t \cdot \tilde{r}_m + (1 - w_t) \cdot r_f$$

- That is, if you expect the market premium to be high, you may invest more in the market portfolio and vice versa.
  - $\hookrightarrow$ What is the beta of r_p at time t?

Potential Benefits of Market Timing

- The ability to time the market can yield great benefits:
  - ↪ If you had put $1 into T-Bills in January 1926, and rolled over the proceeds every month, on January 2003 you would have had in real terms **$21.12.**
  - ↪ If you had put $1 into the value-weighted (VW) index, on January 1, 2003. you would have had **$ 208.25**.
  - ↪ If you switched back and forth on a monthly basis between the bonds and the VW index with *perfect* foresight, on January 1, 2003. **$5.9 million**.
- Of course, no one possesses perfect foresight.
- We can use tools from statistics to assess the degree of predictability in the data.

Market Timing

- Decompose the return on the market into predictable and unpredictable components

$$\tilde{r}_{m,t} = E[r_{m,t}] + \mu_{t-1} + \tilde{e}_{m,t}$$

1. $E[r_{m,t}]$ is the *unconditional* expectation of the market portfolio return.
2. $\mu_{t-1} = E[r_{m,t}|I_{t-1}] - E[r_{m,t}]$ is the (normalized) *conditional* expectation of period t's market portfolio return. This expectation is conditional on information I_{t-1} available in the previous period. This represents the part of next period's return that you can forecast and potentially exploit.
3. $\tilde{e}_{m,t}$ is the surprise component of market portfolio returns. It is *unforecastable* even given the information we possess in the previous period, I_t

Market Timing

- You can vary the β of your portfolio by shifting in and out of the risk-free asset over time. If the beta of your portfolio is $\beta_{p,t-1}$, and the return on your portfolio will be:

$$\tilde{r}_{p,t} - r_{f,t} = \beta_{p,t-1}([E(\tilde{r}_{m,t}) + \mu_{t-1} + \tilde{e}_{m,t}] - r_{f,t}) + \tilde{e}_{p,t}$$

- If, on $\beta_{p,t-1}$ is high when $\tilde{\mu}_{t-1}$ is high, you will earn superior returns. Specifically:

$$E(\tilde{r}_{p,t} - r_{f,t}) = \overline{\beta_{p,t-1}}(E(\tilde{r}_m) - r_f) + cov(\tilde{\mu}_{t-1}, \beta_{p,t-1})$$

where $\overline{\beta_{p,t-1}}$ is the average β of the portfolio.

- *market-timing ability* is the ability to take high market sensitivity (β) positions before the market goes up and low beta positions before the market goes down.

- To implement market timing:

  1. Choose variables, X that should predict market portfolio returns.
  2. Demean the variables: $\tilde{X} = X - E(X)$.
  3. Estimate the following regression:

  $$r_{m,t} = \gamma_0 + \gamma_1 \tilde{X}_{t-1} + e_{m,t}$$

  4. At this point, your forecast of period t market return, *given* the information available at period $t-1$

  $$E(r_{m,t}|X_{t-1}) = \gamma_0 + \gamma_1 \tilde{X}_{t-1}$$

     and $\mu_{t-1} = \gamma_1 \tilde{X}_{t-1}$
  5. Typically the R^2 of this regression will be small, $1-2\%$ for monthly data or $10-14\%$ for annual data.

Predictability

- Variables that have been known to forecast market portfolio returns are
  a) Dividend yield
  b) Earnings - Price Ratio
  c) Short - term interest rate
  d) Slope of Yield Curve
  e) Business Cycle Variables
- If you believe in
  - ↪ ... efficient markets, then the variables that should forecast returns are those that capture changes in *risk* or *risk tolerance*.
  - ↪ ... behavioral theories, then you should include variables that other investors may under- or over-react to (Of course, this is why having a theory helps: just because investors under-reacted in the past does not mean that they will do so again in the future.)

- We estimate a predictive relationship

$$R_{m,t} - r_{f,t} = a + b_{DP}\,DP_{t-1} + b_{EP}\,EP_{t-1} + b_{rf}\,r_{f,t-1} + b_{sl}\,Slope_{t-1} + \varepsilon_{m,t}$$

where

1. DP: Dividend Yield
2. EP: Earnings-Price ratio
3. Slope: 10yr - 3m interest rate
4. r_f: 3m rate
5. R_m: Returns on S&P 500.

- Your best forecast of next period's excess market return will be:

$$\mu_{t-1} = a + b_{DP}\,DP_{t-1} + b_{EP}\,EP_{t-1} + b_{rf}\,r_{f,t-1} + b_{sl}\,Slope_{t-1}$$

Predictability - Example

- Estimation Results

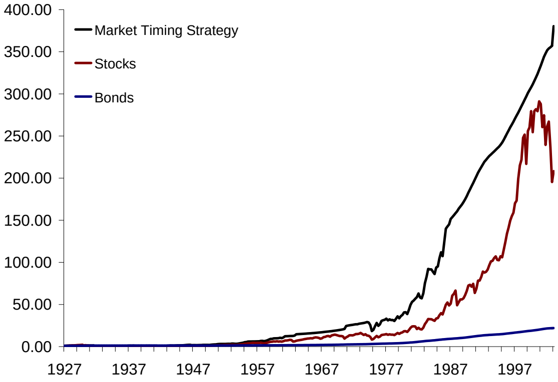
	a	DP	EP	r_f	Slope	R^2
Coeff	0.11	-0.05	0.09	-0.21	-0.03	3.47%
t-stat	2.06	-1.23	2.23	-0.96	-0.06	

- Your best forecast of next period's excess market return will be:

$$\mu_{t-1} = a + b_{DP} DP_{t-1} + b_{EP} EP_{t-1} + b_{rf} r_{f,t-1} + b_{sl} Slope_{t-1}$$

- Suppose that we *knew* of this relationship in 1926 and followed the strategy
  - ↪ $\beta_{p,t-1} = 1$ if $\mu_{t-1} > 0$
  - ↪ $\beta_{p,t-1} = 0$ if $\mu_{t-1} < 0$

Predictability - Example



1926-2002	mean	σ	Sharpe Ratio
Stocks	9.41%	21.31%	29.62%
T-Bills	3.09%		
Market Timing	9.41%	17.59%	35.92%

Caveat: In vs out of sample predictability

- In reality we do not have available data from the future.
- Thus, it is possible that the predictability relation, i.e.

$$E(r_{m,t}|X_{t-1}) = \gamma_0 + \gamma_1 \tilde{X}_{t-1}$$

  is not very stable. That is variables that were able to predict the market portfolio in the past, may not continue to do so in the future.
- In fact, some funds have lost *a lot of* money because statistical relationships that used to hold in the past failed to do so in the future.
- The best defense against this is to have an understanding **why** you should expect this relationship to hold in the future.
  - $\hookrightarrow$ This is where economic theory comes in.

Predictability in Real-Time

- The previous example was not implementable because it used the entire sample to estimate the parameters of the model.
- Let's do this in real time:
  - ↪ At every date t, I use only data available up to date t to estimate

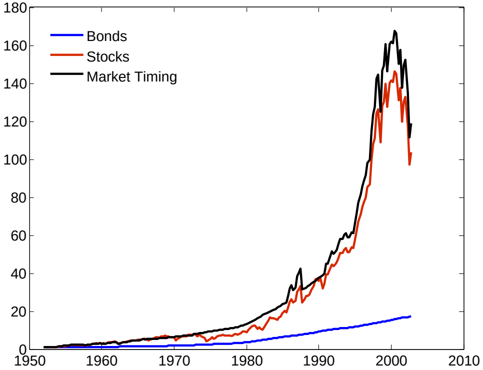
$$R_{m,t} - r_{f,t} = a + b_{DP}\,DP_{t-1} + b_{EP}\,EP_{t-1} + b_{rf}\,r_{f,t-1} + b_{sl}\,Slope_{t-1} + \varepsilon_{m,t}$$

- I form my forecast as before

$$\mu_{t-1} = a + b_{DP}\,DP_{t-1} + b_{EP}\,EP_{t-1} + b_{rf}\,r_{f,t-1} + b_{sl}\,Slope_{t-1}$$

- Use the first third of the sample (1926-1951) to form initial estimates.
- How would I perform in this case?

Predictability - Real Time Example



1952-2002	mean	σ	Sharpe Ratio
Stocks	4.88%	15.92%	30.66%
T-Bills	3.09%		
Market Timing	4.50%	11.14%	40.39%

Efficient Markets and predictability

- Bottom line: return predictability *can* be consistent with efficient markets if it is caused by *changes in risk premia*.
- We saw how to exploit this long-horizon predictability to increase our Sharpe ratios.
- One view is that we should not care if markets are efficient. Whatever the reason is, return predictability seems to be here, so we might as well exploit it.
- However, the reason does matter. If we exploit predictability are we taking on more risk or are we exploiting some inefficiency in the system.

Return predictability and portfolio choice

- Besides changing our allocation to the market portfolio, how does return predictability affect our portfolio choice problem?
- Mean-Variance Analysis, as it was originally formulated was solving *static* problem.
- However, in reality, we can often reoptimize before the end of your investment horizon.
- Reoptimization is useful when the underlying parameters change.

I.i.d. vs non-i.i.d. world

- If the world is i.i.d. (independently and identically distributed) then roptimization has no value.
  - $\hookrightarrow$ The future looks exactly like the past, so if you were investing optimally yesterday, so are you today.
- However, casual empiricism suggests that the world is not i.i.d:
  - $\hookrightarrow$ Expected returns are time-varying.
  - $\hookrightarrow$ Volatility is time-varying.
  - $\hookrightarrow$ Correlations may be time-varying.

Predicting volatility and beta

- So far, we saw how to build a model that predicts expected returns.
- In a similar way, there are models that predict volatilities or betas.
- The models use fairly advanced statistical techniques (e.g. GARCH), so they are outside the scope of this class.
- Nevertheless, they are widely used in practice, especially by option traders.

Period by period MV Optimization

- Once you have estimated conditional means, volatilities and correlations you can plug them into Markowitz and optimize.
- This way, we can be on the *conditional* mean-variance frontier.
- However, we may be able to do better, in utility terms, than period-by-period optimization.
- How? Perhaps we can select a portfolio that delivers high returns when expected returns are high (or low).

Dynamic MV Optimization

- Suppose that you have estimated a predictive model for returns, where

$$
\begin{aligned}
R^i_{t+1} - r_{ft} &= a + bX_t + u_{t+1} \\
\Rightarrow E_t(R^i_{t+1}) - r_{ft} &= a + bX_t
\end{aligned}
$$

- Suppose that X_t is dividend yield, so $b > 0$.
  - $\hookrightarrow$ When X_t is high, future expected returns are high.

- X_t captures variation in investment opportunities.

- Investors may want to hedge changes in investment opportunities depending on their preference, or institutional constraints.

Dynamic MV Optimization

- When X is high, your investment opportunities are better.
- When would you like to hedge changes in X?
  - ↪ You may prefer that your portfolio yields higher returns when X is high, since doing so it allows you to take better advantage of the investment opportunities.
  - ↪ Alternatively, you may prefer your strategy to have lower returns when X is high: since the expected return is higher, you need less money to achieve the same dollar return.
- Such considerations will take you outside the simple mean-variance framework. Merton's ICAPM (1973) is a dynamic extension of the CAPM.

Dynamic MV Optimization

- We saw that the mean-variance optimization framework can be easily adapted to accommodate hedging.
- In the same way that you can hedge
  - ↪ non-traded income, i.e. alumni donations
  - ↪ risks your company is exposed to, i.e. oil prices
  - ↪ illiquid assets that you own, i.e. real estate
- You might also want to hedge variables that drive investment opportunities, by specifying that your target portfolio has a desired correlation with the variable you wish to hedge.

Dynamic MV Optimization

- We solve the same problem as before

$$\min var(R_p) = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j \sigma_{ij}$$

subject to

$$\sum_{i=1}^{N} x_i E_t(R_i) = E(R_p)$$

$$\sum_{i=1}^{N} x_i = 1$$

- but now add the constraint that our portfolio has a target beta b_p^x with changes in investment opportunities.

$$\sum_{i=1}^{N} x_i b_i^x = b_p^x$$

Dynamic MV Optimization and the ICAPM

- Running through similar arguments as the CAPM, Robert Merton derived an intertemporal version, the ICAPM.

- The ICAPM pricing equation is

$$E[R_i] - r_f = \beta_{mkt}\,(E[R_i] - r_f) + b_i^x\,\lambda_x$$

- Stocks differ in their average returns if they
  - $\hookrightarrow$ have different systematic risk (β_{mkt})
  - $\hookrightarrow$ have different exposure to changes in investment opportunities (b_i^x)

- The risk premium λ_x associated with changes in investment opportunities depends on whether investors want to hedge *improvements* or *deteriorations* in investment opportunities.

ICAPM: an example

- Campbell and Vuolteenaho (2004) implemented the following version of the ICAPM:
- Decompose market returns into news about future cashflows and news about future discount rates

$$R_{Mt} = N_{CFt} - N_{DRt}$$

  - $\hookrightarrow$ N_{DRt} corresponds to the component of market return due to predictable movements in discount rates
  - $\hookrightarrow$ N_{CFt} is the residual

ICAPM: an example

- The market beta can be decomposed

$$\beta_{Mi} = \beta_{CFi} + \beta_{DRi}$$

- The ICAPM implies

$$E[R_i] - r_f = \beta_{CFi}\lambda_{CF} + \beta_{DRi}\lambda_{DR}$$

- CV argue $\lambda_{CF} >> \lambda_{DR}$ (Good beta-bad beta)

ICAPM: Good beta, bad beta

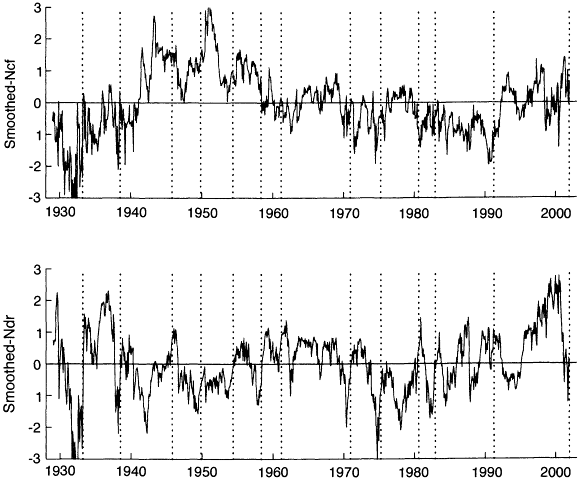


FIGURE 1. CASH-FLOW AND DISCOUNT-RATE RECESSIONS

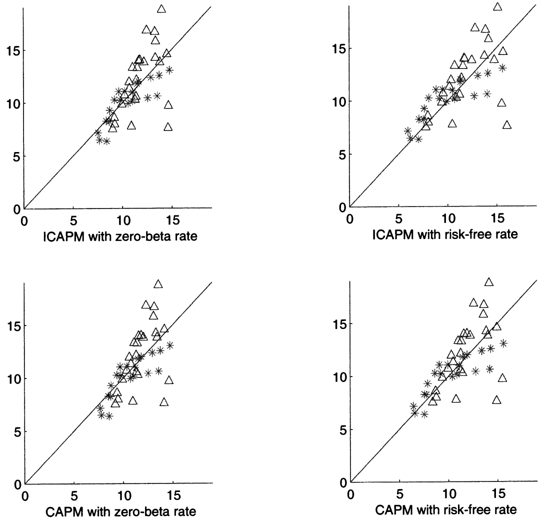
ICAPM: Good beta, bad beta

TABLE 5—CASH-FLOW AND DISCOUNT-RATE BETAS IN THE MODERN SAMPLE

$\hat{\beta}_{CF}$	Growth		2		3		4		Value		Diff.	
Small	0.06	[0.07]	0.07	[0.06]	0.09	[0.05]	0.09	[0.04]	0.13	[0.04]	0.07	[0.04]
2	0.04	[0.06]	0.08	[0.05]	0.10	[0.04]	0.11	[0.04]	0.12	[0.04]	0.09	[0.03]
3	0.03	[0.05]	0.09	[0.04]	0.11	[0.04]	0.12	[0.03]	0.13	[0.04]	0.09	[0.04]
4	0.03	[0.05]	0.10	[0.04]	0.11	[0.03]	0.11	[0.03]	0.13	[0.04]	0.10	[0.04]
Large	0.03	[0.04]	0.08	[0.03]	0.09	[0.03]	0.11	[0.03]	0.11	[0.03]	0.09	[0.03]
Diff.	−0.03	[0.05]	0.02	[0.05]	−0.01	[0.04]	0.02	[0.04]	−0.01	[0.04]		

$\hat{\beta}_{DR}$	Growth		2		3		4		Value		Diff.	
Small	1.66	[0.13]	1.37	[0.11]	1.18	[0.10]	1.12	[0.09]	1.12	[0.10]	−0.54	[0.08]
2	1.54	[0.11]	1.22	[0.09]	1.07	[0.08]	0.96	[0.08]	1.03	[0.09]	−0.52	[0.08]
3	1.41	[0.10]	1.11	[0.08]	0.95	[0.08]	0.82	[0.07]	0.94	[0.09]	−0.47	[0.09]
4	1.27	[0.09]	1.05	[0.08]	0.89	[0.07]	0.79	[0.07]	0.87	[0.08]	−0.41	[0.09]
Large	1.00	[0.07]	0.87	[0.07]	0.74	[0.06]	0.63	[0.07]	0.68	[0.07]	−0.33	[0.08]
Diff.	−0.66	[0.12]	−0.50	[0.11]	−0.44	[0.10]	−0.49	[0.09]	−0.44	[0.08]		

ICAPM: Good beta, bad beta



Summary

- By now, most academics agree that returns are predictable
- The debate has shifted away from market efficiency to the implications of return predictability for asset allocation.
- We can increase our Sharpe ratio by timing the market.
- If the conditional sharpe ratio of the market is time-varying, investors may require higher or lower returns that pay off when the sharpe ratio is high