Lecture 4: Equity Valuation and Market Efficiency

FE-312 Investments

NORTHWESTERN UNIVERSITY

Equity Valuations

- So far, we have framed the entire discussion in terms of returns.
- As far as portfolio decisions are concerned, returns are all that matter!
  - If the price you buy is 'too high' today, this means that your expected return going forward will be lower.
  - An implicit assumption that we made, is that current prices have **no** predictive power for future returns.
  - This would be the case if markets were efficient.
- Nevertheless, we may care about the *level* of prices.

The level of the DJ30 index is a favorite topic of market commentators

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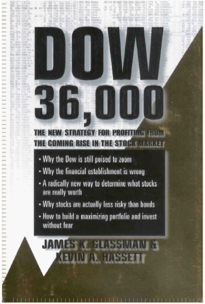
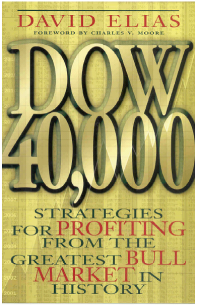
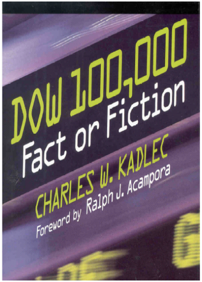
DOW MILESTONES

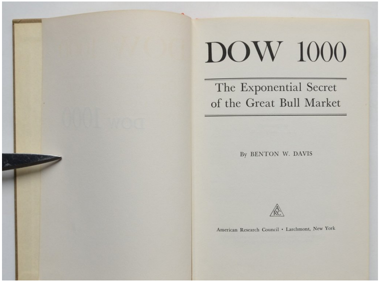
Level	Date	Time needed to reach record
11,000	5/3/99	five weeks
10,000	3/29/99	12 months
9000	4/6/98	8.5 months
8000	7/16/97	5 months
7000	2/13/97	4 months
6000	10/14/96	11 months
5000	11/21/95	9 months
4000	2/23/95	3 years, 10 months
3000	4/17/91	4 years, 3 months
2000	1/8/87	14 years, 2 months
1000	11/14/72	88 years

Many (self-professed) experts like to make predictions

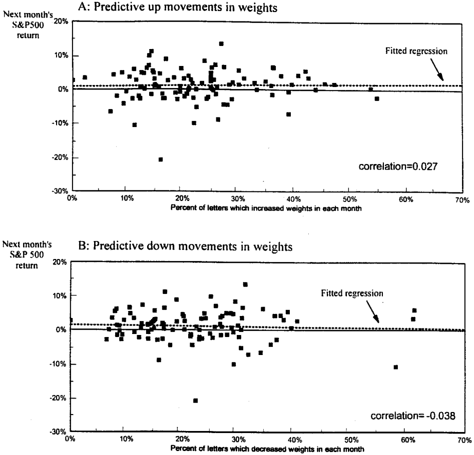








Though most professionals have difficulty timing the market



- Graham and Harvey (1996) examined 237 newsletter strategies. They found no evidence that there is information about future returns

A general model of valuation

- Can we say anything about (current and future) prices?
- Recall the equilibrium relation

$$1 = E[m_1 R_1]$$

  recall that m_1 is a random variable (not necessarily unique) such that the above relation holds for *all* securities; m summarizes all the risk adjustment
- Mechanically, the (gross) return tomorrow can be written as:

$$R_1 = \frac{P_1 + D_1}{P_0}$$

- Plugging into the above and rearranging, we get

$$P_0 = E[m_1 (P_1 + D_1)]$$

- We can recursively substitute P_t using

$$P_t = E[m_{t+1} (P_{t+1} + D_{t+1})]$$

A general model of valuation

- We can recursively substitute P_t gives us

$$P_0 = E[\xi_1 D_1] + E[\xi_2 D_2] + \dots E[\xi_T P_T], \qquad \xi_T = m_1 \times m_2 \times \cdots \times m_T$$
$$= E\left[\sum_{t=1}^{\infty} \xi_t D_t\right] + \underbrace{\lim_{T\to\infty} \xi_T P_T}_{=0 \text{ if no bubbles}}$$

- The value of the stock is simply the present discount value of all dividends
- We can write the value of each piece as

$$E[\xi_t D_t] = E[\xi_t]E[D_t] + cov(\xi_t, D_t)$$
$$= \underbrace{E\left[\frac{D_t}{(1+r_f)^t}\right]}_{\text{'Risk neutral' price}} + \underbrace{cov(\xi_t, D_t)}_{\text{risk adjustment}}$$

where the last equality follows from the fact that $E[\xi_t]$ is the value of a zero coupon bond with maturity t

A general model of valuation

- The previous equation can also be written as

$$P_0 = E^Q\left[\sum_{t=1}^{\infty} \frac{D_t}{(1+r_f)^t}\right]$$

  where the expectation is now take with respect to the 'risk neutral' probabilities

- This version of the formula is common when pricing derivative securities, that is, securities whose payoff depend on events for which you can recover the 'risk-neutral' probabilities from market prices
  - Example: a CDS contract that pays you $1 if the firm goes into default

A model of valuation

- A widely used simplification to the general formula is to assume that

$$\xi_T = \frac{1}{(1+d)^t}$$

- Which gives you a more familiar formula

$$P_0 = E\left[\sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t}\right]$$

- What is r?

- It is the discount rate that ‘appropriately’ adjusts for the risk in cashflows

A model of valuation

- To get some intuition as to what r should be, let's use the definition of a return

$$R_{t+1} = \frac{D_{t+1} + P_{t+1}}{P_t}$$

and work backwards

$$\begin{aligned} P_t &= \frac{D_{t+1}}{R_{t+1}} + \frac{P_{t+1}}{R_{t+1}} \\ &= \frac{D_{t+1}}{R_{t+1}} + \frac{1}{R_{t+1}} \left(\frac{D_{t+2}}{R_{t+2}} + \frac{P_{t+2}}{R_{t+2}} \right) \\ &= \sum_{j=1}^{\infty} \left(\prod_{k=1}^{j} \frac{1}{R_{t+k}} \right) D_{t+j} \end{aligned}$$

A model of valuation

- The price of an asset is equal to the sum of the dividends discounted by returns
- This is an *identity* – it holds exactly when we use *realized* returns and dividends
- We can also apply the expectation operator to both sides to obtain (based on information available at t, so $E_t(P_t) = P_t$),

$$P_t = \sum_{j=1}^{\infty} E_t \left[\left(\prod_{k=1}^{j} \frac{1}{R_{t+k}} \right) D_{t+j} \right] \approx \sum_{j=1}^{\infty} E_t \left[\left(\frac{1}{1+r} \right)^t D_{t+j} \right]$$

with $r = E[R_{t+k}] - 1$

- **Prices and expected returns move in opposite directions**
  - High expected returns mean low prices

A model of valuation

- Yet another way to see this, suppose the security lasts for only one period and take logs

$$
\begin{aligned}
P_t &= \frac{D_{t+1}}{R_{t+1}} \\
p_t &= d_{t+1} - r_{t+1} \\
p_t - d_t &= d_{t+1} - d_t - r_{t+1} \\
p_t - d_t &= E_t[d_{t+1} - d_t] - E_t[r_{t+1}]
\end{aligned}
$$

- High price-dividend ratios today mean either
  - High dividend growth tomorrow
  - Low expected returns
- General version (due to Campbell and Shiller)

$$p_t - d_t = E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j} - E_t \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$$

A model of valuation—Special case

- In the special case where dividend growth is unpredictable, i.e.

$$\frac{D_{t+1}}{D_t} = 1 + \tilde{g}, \qquad g = E[\tilde{g}]$$

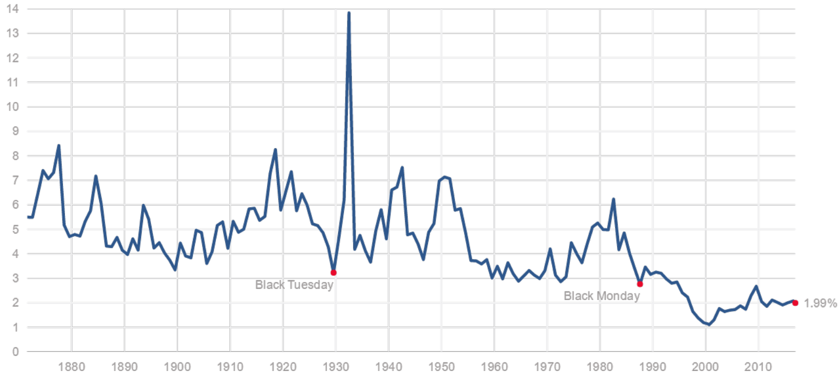
- We get the Gordon Growth formula,

$$\begin{aligned} P_t &= \sum_{j=1}^{\infty} E_t\left[\left(\frac{1}{1+r}\right)^t D_{t+j}\right] \\ &\approx \sum_{j=1}^{\infty} E_t\left[\left(\frac{1+g}{1+r}\right)^t D_t\right] \end{aligned}$$

$$\frac{P_t}{D_t} = \frac{1}{r-g} \Rightarrow \frac{D_t}{P_t} = r - g$$

- The Gordon growth formula is a useful benchmark. It is simple enough that it can be used for back of the envelope calculations.

A model of valuation—Special case



- For the S&P 500, long-run averages are:

$$D/P = 4.5\%; \quad r = 7\%; \quad g = 2.5\%$$

- What assumptions on r and g do you need to get a D/P ratio of 2%?

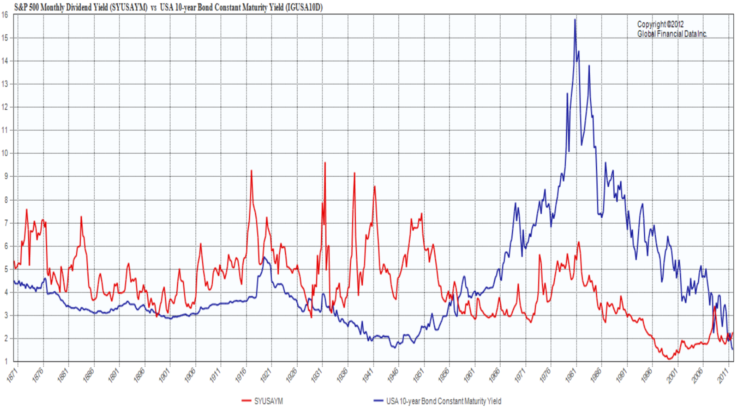
A model of valuation—Special case

- If r and g where constant then so would D/P

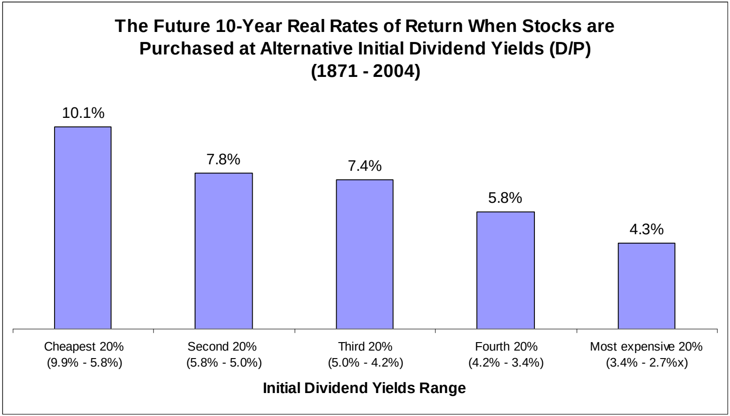
- Put differently, if D/P moves around, it has to be either because it forecasts future returns (r) or it forecasts future dividend growth (g)

- Which of the two is it?

Dividend yield only weakly related to interest rates



Dividend yield predicts future returns



D/P and subsequent 7-Year Stock Returns

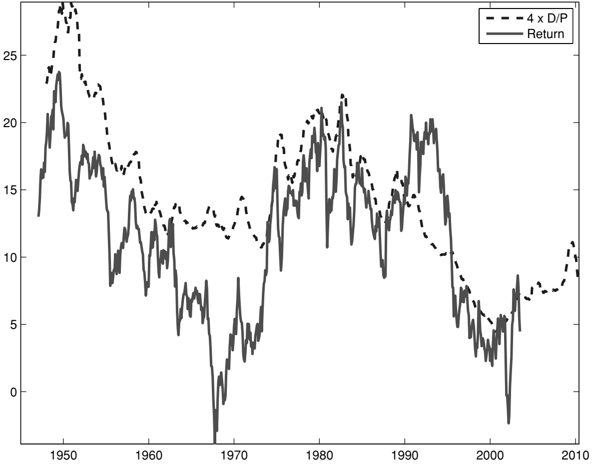
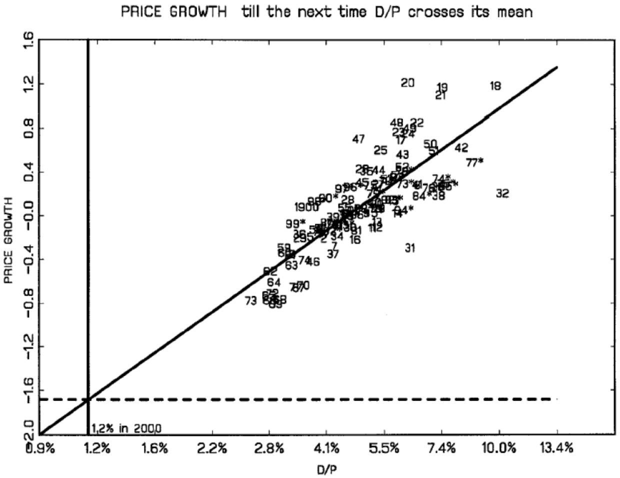


Figure 1. Dividend yield and following 7-year return. The dividend yield is multiplied by four. Both series use the CRSP value-weighted market index.

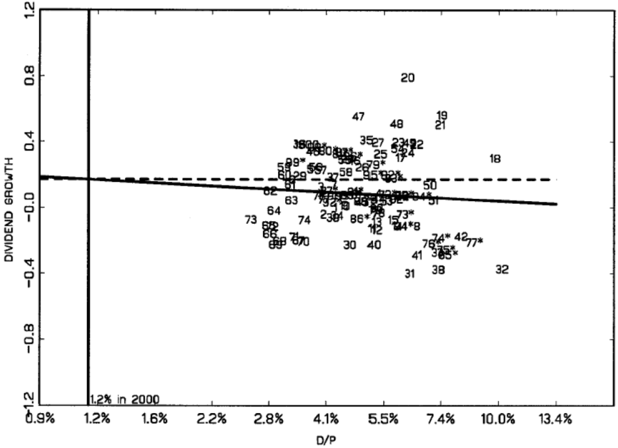
Dividend yield predicts future returns



If D/P is high, then to come back to its mean, either P must rise or D must fall

Dividend yield does not predict future dividend growth

Figure 1. DIVIDEND GROWTH till the next time D/P crosses its mean



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
$r_{t+1} = a_r + b_r(d_t - p_t) + \varepsilon_{t+1}^r$	0.097	1.92	4.0	4.0
$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \varepsilon_{t+1}^{dp}$	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_{t+1}^f 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.

Returns are predictable

The statement that returns are predictable is equivalent to saying that expected returns change over time

$$R_{t+1} = a + bX_t + e_t$$
$$E_t[R_{t+1}] = a + bX_t$$

contrast with $E[R_{t+1}] = a + bE[X_t]$ which is a **constant**

- Q: How "big" is return forecastability? R^2% doesn't look great.
- Answer:
  1. $\sigma(E_t(R_{t+1}))$ is large (6%) compared to $E(R_{t+1})$
  2. R^2 grows quite large at long horizons—predictability 'adds up'

Horizon k	b	t(b)	R^2	$\sigma\left[E_t(R^e)\right]$	$\frac{\sigma[E_t(R^e)]}{E(R^e)}$
1 year	3.8	(2.6)	0.09	5.46	0.76
5 years	20.6	(3.4)	0.28	29.3	0.62

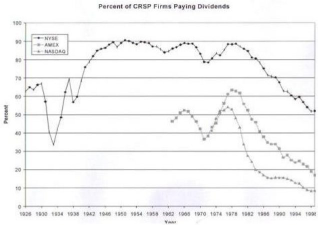
Returns are predictable

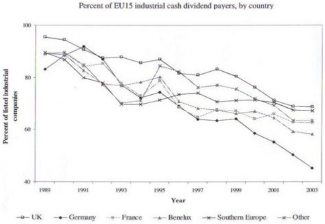
- Most of the variation in D/P seems to come from changes in expected returns.
- Most of these fluctuations are driven by changes in expected returns on stocks — not the risk-free rate
- The following statements are equivalent:
  - Expected returns on stocks (the equity premium) vary over time
  - There is long-term mean reversion in prices
- Whether these temporary fluctuations are driven by rational changes in risk premia or ‘sentiment’ is nearly impossible to disentangle!

Is the current dividend-yield too low?

- At this point, it may be helpful to take a step back.
- Firms have other methods of returning cash to shareholders, e.g. they can buy back shares.
- If you keep the number of shares that you own constant, this will look like a price appreciation (fewer shares $\rightarrow$ price/share will increase).
- But if you keep the *amount* invested constant (i.e. you sell some of your shares) this will look to you like a 'dividend'

Dividends are disappearing

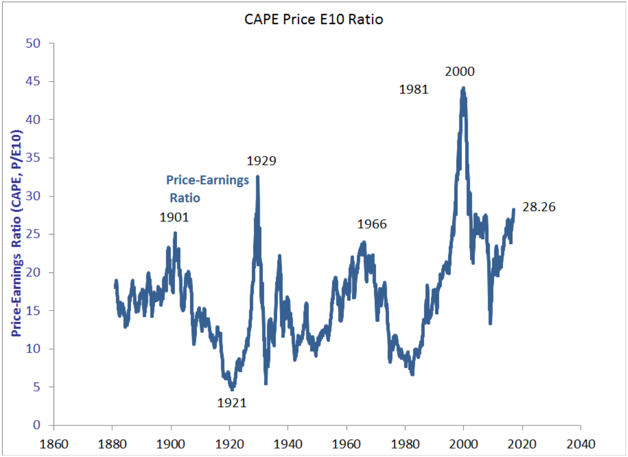




- New firms in general do not pay any dividends

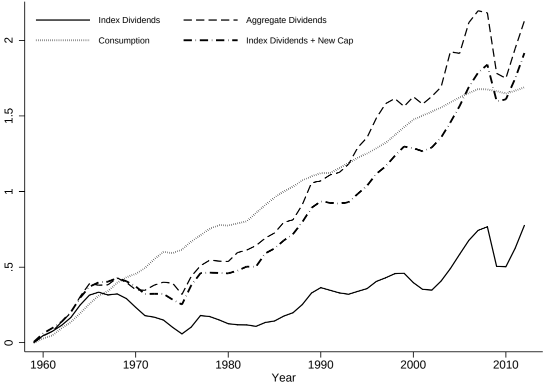
- Many firms have switched from paying cash dividends to repurchaseing shares for tax reasons

Price-Earnings Ratios



- You may think that one way around this is to look at earnings
- Bob Shiller's (Yale) website has data on price/ earnings (technically, 10-year moving average of earnings)

Number of shares is not constant



- But, doing so ignores the fact that the *number* of shares is changing!

Buy and hold vs rebalancing

- If the total number of shares is changing, but you keep the number of shares that you own constant (a buy and hold investor) then the effective fraction of the total stock market that you hold will vary over time.
  - This may explain why returns may look predictable for a buy-and-hold investor $\rightarrow$ the amount of risk that you are bearing changes over time mechanically
- However, an investor who wishes to own the same dollar amount of shares will own the same amount of risk
  - Are returns or 'dividends' (equity payouts) predictable from her perspective?
- To answer this question, we should look at the payout-yield, i.e. the ratio of current equity payout to the value of corporate assets

Payout yield

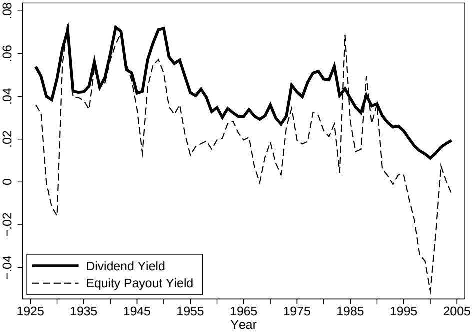


Figure 2: Dividend Yield and Equity Payout Yield
Dividend yield is dividends divided by the CRSP value-weighted index. Equity payout yield is equity payout (i.e., dividends plus equity repurchase minus equity issuance) divided by the market equity of NYSE, AMEX, and NASDAQ stocks.

Source: Larrain and Yogo (2005)

Payout yield

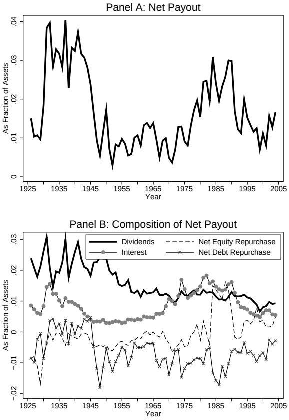


Figure 4: Net Payout Yield in the Flow of Funds
Net payout in Panel A is the sum of dividends, net equity repurchase, interest, and net debt repurchase in Panel B. The data represent nonfinancial corporations in the Flow of Funds for the period 1926–2004.

Source: Larrain and Yogo (2005)

Payout yield

Table 2: Variance Decomposition of Dividend Yield and Equity Payout Yield

In Panel A, the variance of log dividend yield is decomposed into future equity returns, future dividend growth, and future dividend yield. The log-linearization parameter is $\rho = 0.97$. In Panel B, the variance of log equity payout yield is decomposed into future equity returns, future equity payout growth, and future equity payout yield. The log-linearization parameters are $\phi = 0.98$ and $\theta = 2.5$. The last line of each panel reports the standard deviation of expected equity returns and expected cash flow growth in the infinite-horizon present-value model. The sample period is 1926–2004. Estimation is through the VAR reported in Table 1. Point estimates are in bold, and heteroskedasticity-consistent standard errors are in normal text.

	Fraction of Variance in Cash Flow Yield Explained by Future					
Horizon (Years)	Equity Returns		Cash Flow Growth		Cash Flow Yield	
	Panel A: Cash Flow = Dividend					
1	**0.10**	0.05	**0.00**	0.04	**0.90**	0.04
2	**0.18**	0.10	**0.02**	0.07	**0.80**	0.07
5	**0.37**	0.21	**0.07**	0.16	**0.57**	0.14
10	**0.57**	0.30	**0.11**	0.26	**0.32**	0.16
Infinite	**0.83**	0.38	**0.17**	0.38		
Infinite: Std Dev	**0.35**	0.19	**0.08**	0.15		
	Panel B: Cash Flow = Equity Payout					
1	**0.04**	0.02	**0.20**	0.06	**0.76**	0.07
2	**0.07**	0.03	**0.35**	0.10	**0.59**	0.11
5	**0.12**	0.05	**0.61**	0.13	**0.28**	0.14
10	**0.15**	0.06	**0.77**	0.09	**0.08**	0.08
Infinite	**0.16**	0.06	**0.84**	0.06		
Infinite: Std Dev	**0.25**	0.10	**1.27**	0.19		

Source: Larrain and Yogo (2005)

Payout yield

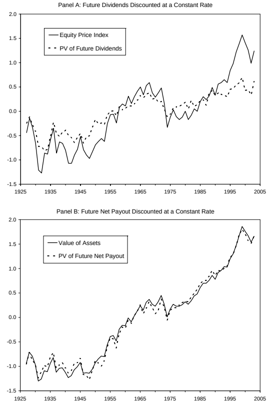


Figure 1: Present Value of Future Dividends and Net Payout
Panel A shows the real value of the CRSP value-weighted index for NYSE, AMEX, and NASDAQ stocks. A VAR in real equity return, real dividend growth, and log dividend yield (reported in Table 1) is used to estimate the present value of dividends under a constant discount rate. Panel B shows the real market value of assets for U.S. nonfinancial corporations. A VAR in real asset return, real net payout growth, and log net payout yield (reported in Table 6) is used to estimate the present value of net payout under a constant discount rate. All series are deflated by the CPI and reported in demeaned log units.

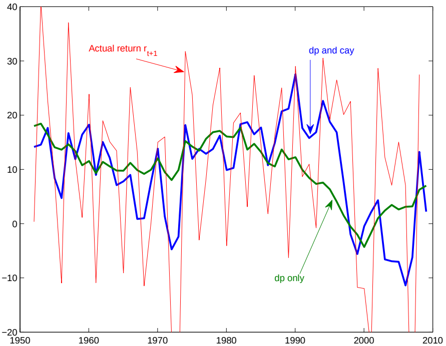
Source: Larrain and Yogo (2005)

Other predictors

- Researchers have uncovered numerous other variables that (supposedly) predict the market
  - short-term interest rates
  - price-earnings ratios (basically, anything that has market prices in it)
  - slope of the yield curve (term spread)
  - oil prices

The consumption-wealth ratio (cay) also forecasts returns

	Coefficients		t-statistics		Other statistics	
Left-hand Variable	dp_t	cay_t	dp_t	cay_t	R^2	$\sigma\left[E_t(y_{t+1})\right]\%$
r_{t+1}	0.12	0.071	(2.14)	(3.19)	0.26	8.99
Δd_{t+1}	0.024	0.025	(0.46)	(1.69)	0.05	2.80
dp_{t+1}	0.94	-0.047	(20.4)	(-3.05)	0.91	
cay_{t+1}	0.15	0.65	(0.63)	(5.95)	0.43	
$r_t^{lr} = \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$	1.29	0.033				0.51
$\Delta d_t^{lr} = \sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}$	0.29	0.033				0.12



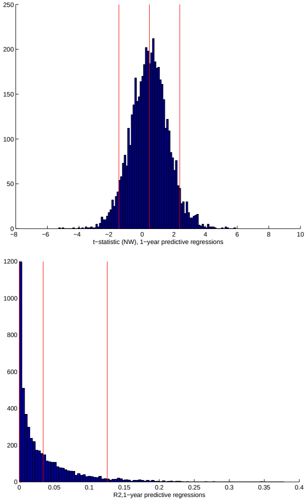
Caveats

- One issue you should be aware of is that these return predictability regressions are not very stable
- With the exception of most of the variables that contain market prices (d/p, cay, etc) the other forecasting relationships are highly dependent on the sample period
- A very important issue is that these forecasting coefficients (and more importantly, the t-statistics and R^2s) are biased in small samples (Stambaugh, 1999)
- The bias arises because
  - Predictor variables are fairly persistent
  - Changes in predictors are correlated with stock returns (change in d/p will be highly correlated with changes in p)
- The bias is worse for long-horizon regressions

Assessing the bias in predictive regressions — MATLAB simulation

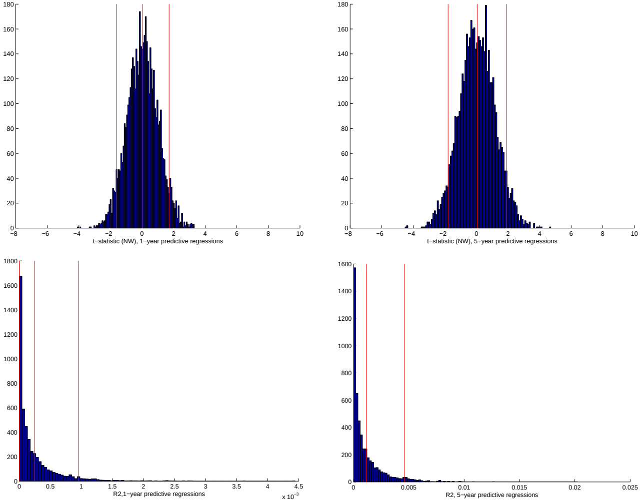
```
T=40
mu=0.07;
rho=0.95;

bXR=-3.5;
sxe=0.02;
sr=0.2;

for isim=1:5000;

xt=zeros(T,1);
rt=zeros(T,1);

xe=normrnd(0,sxe,T,1);
xr=normrnd(0,sr,T,1);

for t=1:T-1

    xt(t+1) = rho* xt(t) + xe(t+1);

    rt(t+1) = mu + xr(t+1) + bXR*xe(t+1); % The last term accounts for the contemporaneous negative correlation between Delta x and r

end

rt5=rt(3:end-4) + rt(4:end-3) + rt(5:end-2) + rt(6:end-1) + rt(7:end); % Accumulate returns
rt1=rt(3:end-4);

stdr(isim)=std(rt);
corr_rx(isim)=corr(rt(2:end),diff(xt));

[b,bint,r,rint,s]=regress(rt5,[ones(size(rt5)) xt(2:end-5)]);
rsq5(isim)=s(1);
b5(isim)=b(2);

[b,bint,r,rint,s]=regress(rt1,[ones(size(rt5)) xt(2:end-5)]);
rsq1(isim)=s(1);
b1(isim)=b(2);

end
```

Bias in predictive regressions — MATLAB simulation



Sample size: $T = 40$ years. Red lines indicate means, 5% and 95% cutoffs across simulations

Bias in predictive regressions — MATLAB simulation



Sample size: $T = 4,000$ years. Red lines indicate means, 5% and 95% cutoffs across simulations

Bottom line

- Return predictability is (still) a hotly debated topic
- Economic theory suggests that returns *can* be predictable
- Statistically however, it is difficult to detect in short samples.
- Perhaps the most compelling evidence in favor of return predictability is that the dividend yield is quite volatile
  - If r and g are constant then d/p will also be constant
  - high prices (low d/p) does not forecast high dividend growth (g seems constant) so on some level it has to forecast low future market returns
- If you want to take advantage of predictability
  - Use predictive variables motivated by economic theory
  - Be aware of statistical issues

Why might returns vary over time?

- What determines expected returns?
- Investors dislike risk
- So when risk is high, we should demand high returns

Asset market equilibrium

- Under the CAPM, everybody holds a mix of the market portfolio ($E[r_m] = \bar{r}_m$, variance=σ_m^2) and the risk-free asset

- If assets are in fixed supply (there are a certain number of shares of the stock market and bonds outstanding in the world), then w_m – weight on the market – is fixed
  - I.e. portfolio weights must add up so that the market clears and somebody owns the available assets

- Recall:

$$w_m = \frac{\bar{r}_m - r_f}{A\sigma_m^2}$$

Asset market equilibrium

$$w_m = \frac{\bar{r}_m - r_f}{A\sigma_m^2}$$

- w_m is fixed by the supply of assets
- σ_m^2 is determined by fundamental risks (i.e. dividend volatility)
- So $\bar{r}_m$ is determined in equilibrium by the other variables
- As A, σ_m^2, or r_f moves, $\bar{r}_m$ will also have to move
    - We usually assume w_m is constant
    - One way to forecast returns: forecast A or σ_m^2

Forecasting market returns

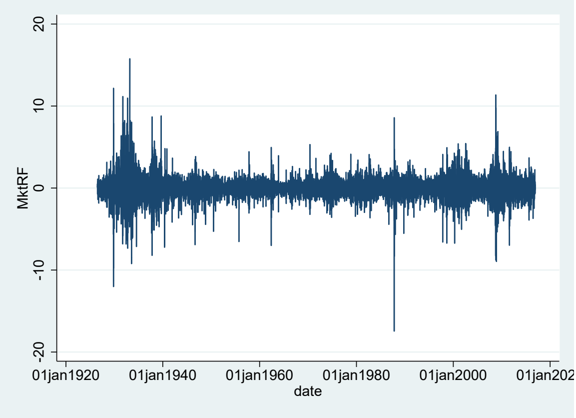
$$1 = w_m = \frac{\bar{r}_m - r_f}{A\sigma_m^2} \Rightarrow \bar{r}_m - r_f = A\sigma_m^2$$

- If all investors are mean-variance optimizers:
  - An increase in average risk aversion raises the market risk premium
  - An increase in market volatility raises the market risk premium
  - Both imply higher *future* returns but reduce prices today

Historical daily market returns

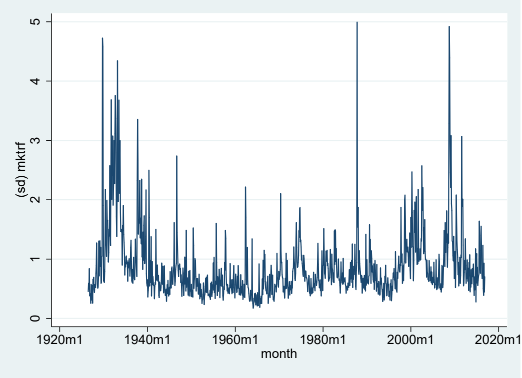
Using Stata:

```
use "DailyMarketReturns.dta", clear
tsset date
tsline mktrf
```



Volatility is clustered

```
use "DailyMarketReturns.dta", clear

gen month=mofd(date)
format %tm month

collapse (sd) mktvol=mktrf, by(month)
tsset month
tsline mktvol
```



Volatility is highly persistent

```
. corr mktvol L.mktvol
(obs=1,084)

             |                  L.
             |   mktvol   mktvol
-------------+------------------
      mktvol |
         --. |   1.0000
         L1. |   0.7122   1.0000
```

Changes in volatility are negatively correlated with the market

```
. merge 1:1 month using "MonthlyMarketReturns.dta"

. gen logvol=log(mktvol)

. corr mktrf D.logvol
(obs=1,084)

             |                 D.
             |    mktrf   logvol
-------------+------------------
       mktrf |   1.0000
      logvol |
         D1. |  -0.3348   1.0000
```

But volatility does not predict future market returns

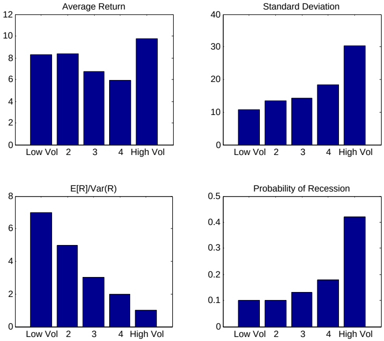
```
. reg mktrf L.mktvol

      Source |       SS           df       MS      Number of obs   =     1,084
-------------+----------------------------------   F(1, 1082)      =      0.03
       Model |  .987743658         1  .987743658   Prob > F        =    0.8534
    Residual |   31273.708     1,082  28.9036118   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0009
       Total |  31274.6957     1,083  28.8778354   Root MSE        =    5.3762

------------------------------------------------------------------------------
       mktrf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      mktvol |
         L1. |  -.0509479   .2756004    -0.18   0.853    -.5917197     .489824
             |
       _cons |   .6936888   .2908815     2.38   0.017     .1229331    1.264445
------------------------------------------------------------------------------

. reg mktrf L.logvol

      Source |       SS           df       MS      Number of obs   =     1,084
-------------+----------------------------------   F(1, 1082)      =      0.00
       Model |  .041950285         1  .041950285   Prob > F        =    0.9696
    Residual |  31274.6537     1,082  28.9044859   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0009
       Total |  31274.6957     1,083  28.8778354   Root MSE        =    5.3763

------------------------------------------------------------------------------
       mktrf |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      logvol |
         L1. |   .0118588   .3112833     0.04   0.970    -.5989285    .6226461
             |
       _cons |    .652623   .1865299     3.50   0.000     .2866216    1.018624
------------------------------------------------------------------------------
```

Volatility-managed portfolios

- We saw two important facts:
  1. Volatility is highly persistent
  2. Volatility does not forecast future market returns very well
- What this implies is that we should *reduce* our allocations to stocks when volatility is high (and increase them when volatility is low)
  - That is, you should an allocation to stocks proportional to
    $$w_t = \frac{\mu - r_f}{\hat{\sigma}_t^2}$$
    where $\hat{\sigma}_t^2$ is your forecast of the variance next period
- Practitioners call this a *volatility managed portfolio*

Volatility-managed portfolios

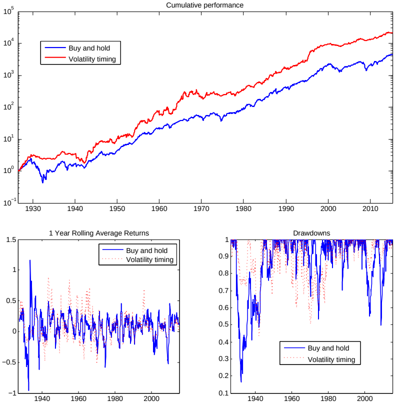
Figure 1: Sorts on previous month's volatility. We use the monthly time-series of realized volatility to sort the following month's returns into five buckets. The lowest, "low vol," looks at the properties of returns over the month *following* the lowest 20% of realized volatility months. We show the average return over the next month, the standard deviation over the next month, and the average return divided by variance. Average return per unit of variance represents the optimal risk exposure of a mean variance investor in partial equilibrium, and also represents "effective risk aversion" from a general equilibrium perspective (i.e., the implied risk aversion, γ_t, of a representative agent needed to satisfy $E_t[R_{t+1}] = \gamma_t \sigma_t^2$). The last panel shows the probability of a recession across volatility buckets by computing the average of an NBER recession dummy. Our sorts should be viewed analagous to standard cross-sectional sorts (i.e., book-to-market sorts) but are instead done in the time-series using the past months realized volatility.



Source: Morreira and Muir (2016)

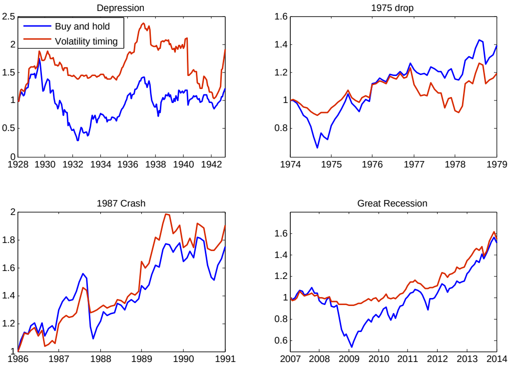
Volatility-managed portfolios

Figure 3: Cumulative returns to volatility timing for the market return. The top panel plots the cumulative returns to a buy-and-hold strategy vs. a volatility timing strategy for the market portfolio from 1926-2015. The y-axis is on a log scale and both strategies have the same unconditional monthly standard deviation. The lower left panel plots rolling one year returns from each strategy and the lower right panel shows the drawdown of each strategy.



Source: Morreira and Muir (2016)

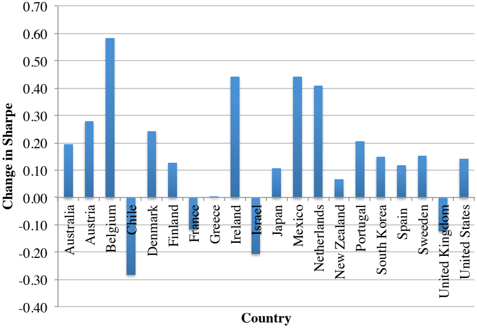
Figure 5: Volatility timing performance during large market downturns. The figure plots the performance of our volatility timing strategy compared to a buy-and-hold strategy for the market return during specific episodes of market turmoil where there was also a large stock market drop.



Source: Morreira and Muir (2016)

Volatility-managed portfolios

Figure 8: Increase in volatility managed Sharpe ratios by country. The figure plots the change in Sharpe ratio for managed vs non-managed portfolios across 20 OECD countries. The change is computed as the Sharpe ratio of the volatility managed country index minus the Sharpe ratio of the buy and hold country index. All indices are from Global Financial Data. For many series, the index only contains daily price data and not dividend data, thus our results are not intended to accurately capture the level of Sharpe ratios but should still capture their difference well to the extent that most of the fluctuations in monthly volatility is driven by daily price changes. All indices are converted to USD and are taken over the US risk-free rate from Ken French. The average change in Sharpe ratio is 0.15 and the value is positive in 80% of cases.

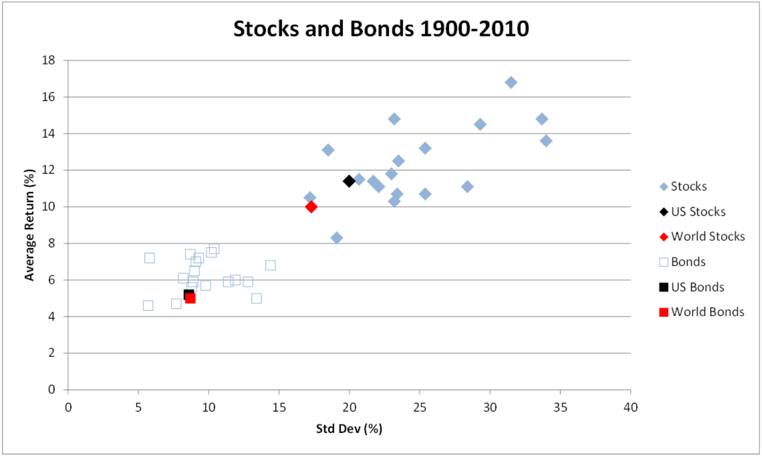


Source: Morreira and Muir (2016)

Volatility-managed portfolios

- What do these results mean?
- If you care about short-term fluctuations in volatility you can do **much** better by timing volatility
- Does this mean there is no reward for increased risk? Not necessarily, maybe there is no reward for increased *short-term* volatility
- Recall that volatility is persistent, but not *that* persistent
  - Monthly autocorrelation coefficient is 0.7, implying shocks have a half-life of 2 months

Risk and return over the long-run



Summary

- Prices should equal the NPV of future cashflows
- High prices seem to be followed by low future returns
  - though statistically it is hard to reject that this isn't the case...
- High (short-run) volatility does not seem to predict high future returns
  - if you care about short-term losses you might want to reduce your allocation to stocks