Asset and Risk Management I

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Measurement and Management of Portfolio Risks

Portfolio management and portfolio risk management

- Portfolio management necessarily incorporates a risk perspective in the decision-making process, as
  - clients are commonly risk-averse (e.g., mean-variance efficiency, higher moments) and
  - performance measures are commonly risk-adjusted (e.g., Sharpe ratios, benchmark portfolios).
- Despite this close relation, risk management is usually situated with distinct individuals.
  - Combining both roles can lead to severe agency problems.
  - Specialization and independence can additionally boost the analyses' quality.

Arguments for risk management's independence

- Apart from regulatory requirements for separation, there are good reasons for independent risk management in asset management:
  - incentive conflicts of portfolio managers (traders essentially own a call option),
  - independent oversight over allocation decisions (limiting legal risks, detecting fraud), and
  - risk forecasts are inherently different from return forecasts.
- Risk management requires a complete and thorough analysis. Simply applying statistical models is insufficient to capture the dynamic economic environment of the future.
- Naively following risk models is itself risky.

Agenda

- Portfolio risk measures
  - return distributions and covariance estimation
  - volatility, Value-at-Risk (VaR), and expected shortfall (ES)
- Risk factors and risk types overview
  - statistical risk factors, industry and country risk, macroeconomic risk, security characteristics and risk factors, FX risk, credit risk, transaction costs and liquidity risk, operational risk

Recommended reading:

Connor, Goldberg, & Korajczyk (2010)

Portfolio Risk Measures

Returns

- The starting point is **returns** R, where arithmetic (net) returns are as defined as

$$R_t = \frac{P_t + CF_t}{P_{t-1}} - 1.$$

- The returns is a **random variable**, as is the price P_t and the interim cash flows CF_t.
- We use $\mathbf{R}$ to denote the n-vector of returns.
- We can aggregate individual asset returns to portfolio returns with the portfolio's weight vector $\mathbf{w}$, i.e.,

$$R_w = \mathbf{w}'\mathbf{R}.$$

- Returns are measured at different **frequencies**, which compound to other frequencies.

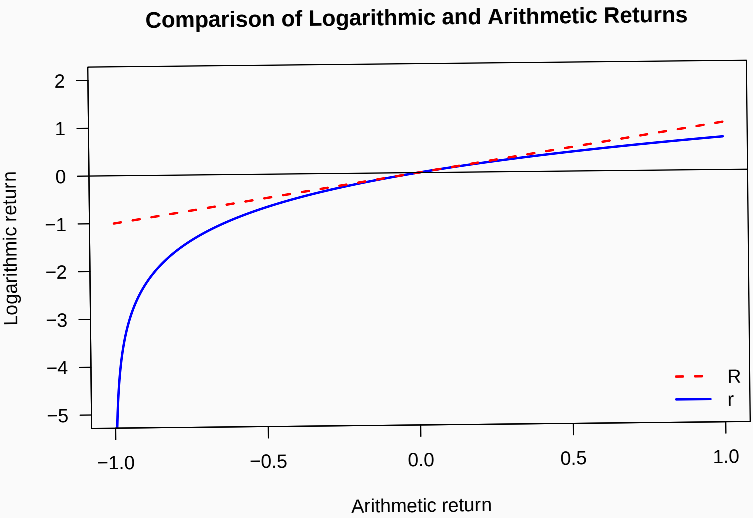
Log returns

- In many applications **log returns** are a useful concept

$$r_t = \log(P_t + CF_t) - \log(P_{t-1}) = \log(1 + R_t).$$

- Log returns are additive over time and facilitate temporal aggregation of risk.
  - For serially uncorrelated returns, the variance of the T-period log return is the sum of the variances of the one-period returns.
- Yet, log returns cannot be added linearly in a portfolio and are less attractive for stating investment objectives.

Illustration



Excess returns

- In risk management (as in asset management more generally), **excess returns** are typically preferable. In a portfolio, excess returns can be defined as

$$Rx_w = \mathbf{w}'\mathbf{Rx} = \mathbf{w}'\mathbf{R} - R_f = \begin{pmatrix} \mathbf{w} \\ -1 \end{pmatrix}' \begin{pmatrix} \mathbf{R} \\ R_f \end{pmatrix},$$

  where R_f is the risk-free rate.

- Excess log returns are usually defined as $rx = \log\left((1+R)/(1+R_f)\right) = r - r_f$.

Active returns

- Large institutional investors typically allocate funds to asset class-specific managers that are **benchmarked** against an appropriate index.
- The difference between the benchmark and the manager's return is the **active return**.
- Let $\mathbf{w_B}$ denote benchmark portfolio weights, then the **active portfolio weight** is

$$\mathbf{w_A} = \mathbf{w} - \mathbf{w_B}.$$

- The active framework imposes a zero-cost constraint $\mathbf{w}_\mathbf{A}'\mathbf{1^n} = 0$.
- The active return is the difference of two returns on unit-cost portfolios.

Return distribution and moments

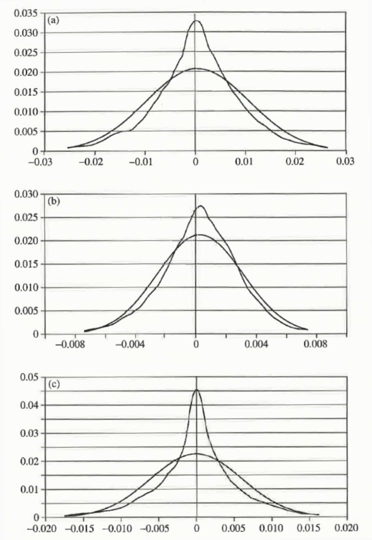
- The most general notion of portfolio risk is the **return distribution** of r, with cumulative density function (CDF)

$$F(x) = \Pr(r \leq x),$$

with an associated probability density function (PDF) $f(x)$.

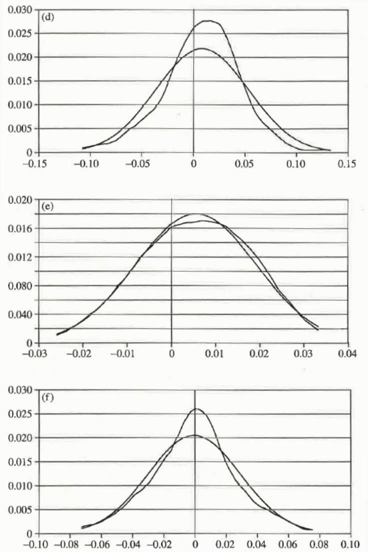
- In principle, this is all information ever needed for risk management.
- **Variance** is the most common risk metric. It's square root – the standard deviation – is the volatility of a return series.
- **Skewness** and **kurtosis** are the third and fourth central moments of the standardized returns.

Example: one-day return distributions



US stocks, US bonds, sterling-dollar. Source: Connor, Goldberg, & Korajczyk (2010).

Example: 20-days return distributions



US stocks, US bonds, sterling-dollar. Source: Connor, Goldberg, & Korajczyk (2010).

Portfolio variance and asset covariance matrix

- We already discussed the portfolio variance computed with the asset covariance matrix $\mathbf{C}$, i.e.,

$$\sigma_w^2 = \mathbf{w}'\mathbf{C}\mathbf{w}.$$

  - Recall the issues in estimating the covariance matrix's components and
  - that factor models can reduce the complexity of the parameters.
- Higher order moments can also be constructed for portfolio returns and can be useful in certain scenarios.
  - Do most investors prefer positive or negative skewness?
  - Do most assets exhibit positive or negative skewness? How relevant is this in a portfolio context?
  - What about kurtosis?

Example return moments

Period	Volatility	Skewness	Excess kurtosis
Stock market index			
1-day	1.04×10^{-4}	−1.2104	28.03
5-day	5.72×10^{-4}	−0.9837	14.13
20-day	2.02×10^{-3}	−0.6447	7.18
Bond market index			
1-day	2.83×10^{-3}	0.0108	4.82
5-day	3.98×10^{-5}	−0.0806	1.27
20-day	1.87×10^{-4}	−0.0214	1.37
Sterling-dollar foreign exchange return			
1-day	0	−0.1113	4.44
5-day	1.95×10^{-4}	−0.0900	3.19
20-day	8.71×10^{-4}	0.2555	1.80
Market insurance provision			
1-day	3.30×10^{-5}	−32.8600	1,994.09
5-day	1.12×10^{-4}	−14.5140	400.35
20-day	6.81×10^{-4}	−5.5170	117.35

Source: Connor, Goldberg, & Korajczyk (2010).

Value-at-Risk

- Observed return distributions often deviate from normality.
  - There are too many inliers (returns close to 0) and outliers (extreme returns).
  - Large losses tend to outnumber large gains.
- Hence, measures that characterize these departures can be useful to complement variance.
- The **Value-at-Risk** (VaR) is defined as

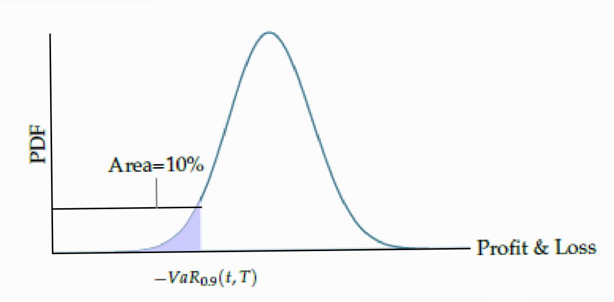
$$\Pr(-R \geq \text{VaR}) = \alpha,$$

  where $1-\alpha$ is the **confidence level**, typically 95% or 99%.
- The α% Value-at-Risk of a unit-cost portfolio is the level of (negative) return such that the cumulative probability of a larger-magnitude negative return equals α.

Value-at-Risk

- The VaR can be expressed in percent or in currency units.
- The VaR in € is the amount such that the probability of losing this or a higher amount over a given time horizon is equal to $\alpha\%$.
  - With probability $1 - \alpha\%$, the loss will be smaller than € VaR.
  - With probability $\alpha\%$, the loss will be larger than € VaR.
- To calculate the VaR in €, one typically (i) calculates first the exposure the the risk factor(s), (ii) computes the VaR in % of the risk factor, and finally (iii) obtains the product which is the Var in €.
- If there are several risk factors, one has to take into account the correlations between them.

Illustration



For a continuous random variable, the VaR is determined by the abscissa at which the area below the PDF equals the level $1-\alpha$. Source: Ballotta, L. and G. Fusai (2017), A Gentle Introduction to Value at Risk, Figure 2.

Example with a single risk factor

- You are a Euro-based investor and own USD 10 million in cash. The current exchange rate $S_t^{USD/EUR} = 1.25$. The standard deviation of the daily spot rate is 0.565% and approximately normally distributed. Calculate the VaR with a horizon of 10 business days and a 95% confidence.
- Solution:
  - Your exposure is € 8 million.
  - The 10-day standard deviation equals $0.565\% \times \sqrt{10} = 1.787\%$.
  - The 95% percent VaR is given by 1.65 times this number, or 2.95%.
  - Hence, the VaR equals €236,000.

Example with two risk factors

- Now assume you hold USD 10 million in U.S. treasuries. The bond standard deviation is equal to 0.605%, and the bond returns and USD changes have a correlation of -0.27. Calculate the VaR.
- Solution:
  - FX risk is €236,000, as calculated above.
  - Interest rate risk is 8 mn $\times 1.65 \times 0.605\% \times \sqrt{10} = e252,540$.
  - Total VaR = €295,447 $= \sqrt{236000^2 + 252,540^2 + 2 \times 236000 \times 252,540 \times -0.27}$

Methods for VaR calculation

- Financial returns typcially do not follow a normal distribution. And portfolios often contain nonlinear instruments.
- The most common methods to compute the VaR are:
  - Delta-Normal. The linear exposure is estimated (for options, the delta), and normal distribution of risk factors assumed.
  - Historical simulation. The current portfolio is valued using returns from a large number of different historical time windows.
  - Monte Carlo simulation. The current portfolio is valued using many return paths generated using defined stochastic processes.

Expected Shortfall

- When a large loss occurs, how large will it be?
- An important complement to Value-at-Risk is the **Expected Shortfall** (ES) defined as

$$\text{ES} = \mathbb{E}[-R \mid -R \geq \text{VaR}].$$

- Therefore, the expected shortfall is the expected loss given that a Value-at-Risk limit is breached.
- By definition, ES exceeds the VaR, with the distance potentially being large.

Example Value-at-Risk and Expected Shortfall

Period	VaR^{95}	VaR^{95} normal	VaR^{99}	VaR^{99} normal	ES^{95}	ES^{95} normal	ES^{99}	ES^{99} normal
Stock market index								
1-day	0.0155	0.0164	0.0256	0.0233	0.0228	0.0207	0.0376	0.0269
5-day	0.0356	0.0373	0.0570	0.0536	0.0517	0.0473	0.0854	0.0619
20-day	0.0597	0.0658	0.1083	0.0965	0.0982	0.0846	0.1647	0.1121
Bond market index								
1-day	0.0044	0.0044	0.0074	0.0063	0.0063	0.0056	0.0095	0.0073
5-day	0.0872	0.0090	0.0152	0.0133	0.0126	0.0117	0.0179	0.0155
20-day	0.0166	0.0170	0.0261	0.0263	0.0233	0.0227	0.0356	0.0311
Sterling–dollar foreign exchange return								
1-day	0.0099	0.0100	0.0175	0.0141	0.0148	0.0125	0.0229	0.0163
5-day	0.0225	0.0232	0.0380	0.0327	0.0327	0.0290	0.0490	0.0376
20-day	0.0489	0.0493	0.0731	0.0694	0.0641	0.0616	0.0838	0.0797
Market insurance provision								
1-day	0.0028	0.0092	0.0081	0.0131	0.0083	0.0116	0.0233	0.0151
5-day	0.0055	0.0168	0.0177	0.0244	0.0187	0.0214	0.0543	0.0282
20-day	0.0004	0.0047	0.0025	0.0108	0.0030	0.0084	0.0104	0.0139

Source: Connor, Goldberg, & Korajczyk (2010).

Risk Factors

Introduction

- There are many risk factors to consider in an asset management context.
- **Statistical factor** analysis is a starting point for many other models.
- Nevertheless, there are many risk factors and associated models to be covered
  - Industry and country risk,
  - Macroeconomic risk and FX risk,
  - Credit risk,
  - Transaction costs and liquidity risk, and
  - Operational risk.
- Recall that security characteristics can be used as risk factors.

Statistical Factors

Statistical factors: linear decomposition

- Before jumping into any factor model, a linear return decomposition is a useful first step, i.e.,

$$\mathbf{Rx} = \mathbf{a} + \mathbf{Bf} + \varepsilon,$$

  - where $\mathbf{B}$ is an $n \times k$ matrix of factor betas,
  - $\mathbf{f}$ is a k-vector of factor returns, and
  - ε is a n-vector of asset-specific returns.
- Set $\mathbf{a}$ such that $\mathbb{E}[\varepsilon] = \mathbf{0}$.
- Defining $\mathbf{B}$ appropriately (i.e., $\mathbf{B} = \text{cov}(\mathbf{Rx}, \mathbf{f})\mathbf{C}_f^{-1}$) implies that $\text{cov}(\mathbf{f}, \varepsilon) = \mathbf{0}^{k \times n}$.
- Returns are unrestricted in the general case only requiring finite variances.
- As only the product $\mathbf{Bf}$ affects returns, they are **rotationally indeterminate**.

Statistical factors: strict factor model

- The linear factor decomposition also means that the covariance matrix can be decomposed as

$$\mathbf{C} = \mathbf{B}\mathbf{C}_{\mathbf{f}}\mathbf{B}' + \mathbf{C}_{\varepsilon}.$$

- The **strict factor model** assumes that idiosyncratic returns are cross-sectionally uncorrelated, i.e.,

$$\mathbf{C}_{\varepsilon} = \mathrm{Diag}\left[\sigma^2_{\varepsilon_1}, \dots, \sigma^2_{\varepsilon_n}\right].$$

- In a well-diversified portfolio (i.e., $\mathbf{w}'\mathbf{w} \approx 0$), a strict factor model implies zero asset-specific risk (Ross, 1976).

Statistical factors: Principal Components

- Principal components analysis (PCA) orders linear combinations of assets by their contributions to variance.
- For any symmetric positive-definite matrix $\mathbf{C}$ with rank $n \geq k$ we can perform an eigenvector decomposition,

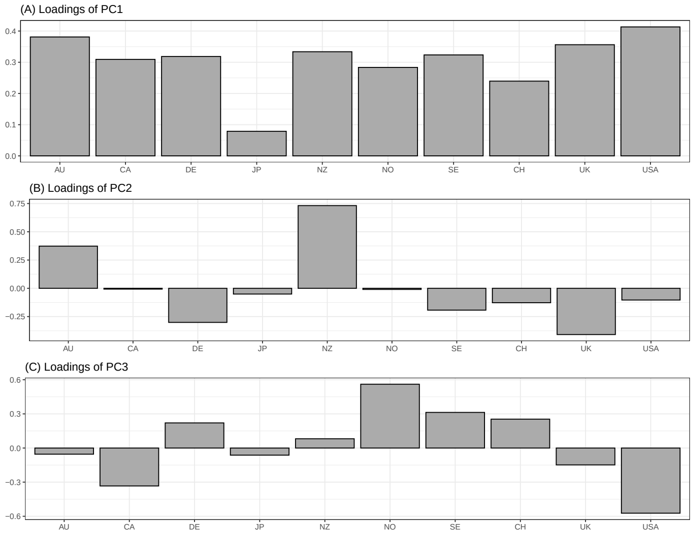
$$\mathbf{C} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}',$$

  where $\mathbf{\Lambda}$ is a $(n \times n)$ diagonal matrix of eigenvalues (ordered from largest to smallest).
- The first k eigenvectors scaled by the square roots of their eigenvalues $(\mathbf{V_k}\mathbf{\Lambda_k}^{1/2})$ are called the k **principal components** (PC).

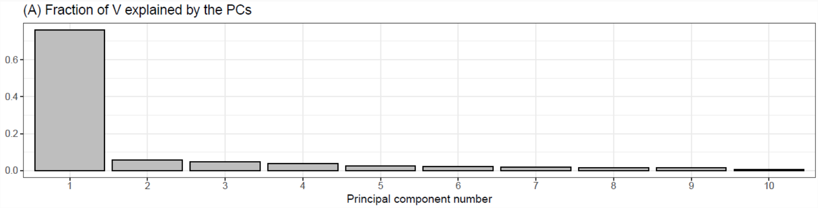
Statistical factors: Principal Components

- By isolating the largest eigenvalues of the covariance matrix, the PCA gives a lower-dimensional approximation to this matrix.
- PC1 is the linear combination (with norm 1) that captures the most common variation across assets. The second PC is orthogonal to PC1, and captures the second most common variation. Etc.
- We know that the precision of high-dimensional covariance matrices is problematic. PCA can be used to reduce the dimensionality and construct more robust covariance matrices. This is important for risk management.

Example: PCA on international bond returns

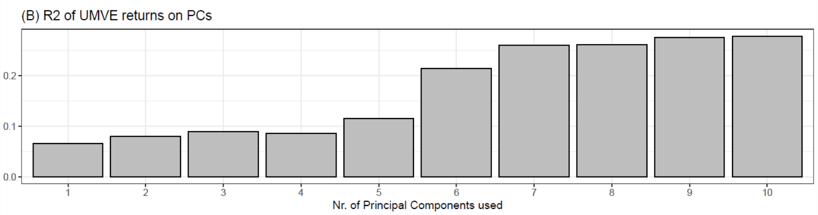


The factor structure of international bond portfolios



- The first 3 Principal Components (PCs) explain around 86% of the variation in bond returns.

The optimal bond portfolio is not spanned by the PCs



- Remark: In this analysis, the first 10 PCs explain less than 30% of the optimal bond portfolio returns.

PCA: advantages and limitations

Advantage:

- The first few (often 3) PCs will explain most of the total return variation.
- This provides a huge reduction in dimensionality.

Problems:

- PCA does not capture time variation in risk loadings.
- Standard PCA ignores expected returns — only focuses on risk.
- According to APT, risk factors should carry a risk premium.

Solution:

- Newer methods (e.g., RP-PCA) combine information on joint variability and average returns to identify factors.

Other Factors

Industry and country risk

- Estimating country and industry risk factors is of paramount importance for assessing a global portfolio's riskiness.
- In particular, many benchmarks do not consider the global perspective.
  - This adds unaccounted risk to active returns creating unsatisfactory controls and potential agency conflicts.
- Additionally, corporate bond markets have expanded across industries and countries.

Example industry risk

	NDs	Dur.	Man.	En.	HiTec	Tel.	Shops	Health	Util.	Other
NDs	1.00	0.42	0.39	0.44	0.31	0.3	0.38	0.47	0.51	0.53
Dur.		1.00	0.66	0.33	0.53	0.38	0.5	0.61	0.55	0.57
Man.			1.00	0.38	0.49	0.34	0.52	0.71	0.49	0.55
En.				1.00	0.29	0.26	0.33	0.43	0.46	0.44
HiTec					1.00	0.36	0.5	0.45	0.43	0.38
Tel.						1.00	0.38	0.39	0.34	0.38
Shops							1.00	0.49	0.41	0.47
Health								1.00	0.61	0.62
Util.									1.00	0.61
Other										1.00

Monthly data covering the period January 1975 to December 2007. Data courtesy of Ken French. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for details of industry portfolio construction.

Source: Connor, Goldberg, & Korajczyk (2010).

Example country risk

	AU	FR	GER	HK	IT	JAP	SP	SW	U.K.	U.S.
AU	1.00	0.42	0.37	0.46	0.30	0.32	0.39	0.44	0.51	0.49
FR	0.42	1.00	0.67	0.35	0.52	0.41	0.51	0.62	0.58	0.52
GER	0.39	0.66	1.00	0.38	0.48	0.35	0.51	0.70	0.51	0.50
HK	0.44	0.33	0.38	1.00	0.30	0.29	0.32	0.42	0.47	0.44
IT	0.31	0.53	0.49	0.29	1.00	0.35	0.49	0.41	0.42	0.35
JAP	0.30	0.38	0.34	0.26	0.36	1.00	0.38	0.43	0.38	0.31
SP	0.38	0.50	0.52	0.33	0.50	0.38	1.00	0.44	0.43	0.42
SW	0.47	0.61	0.71	0.43	0.45	0.39	0.49	1.00	0.61	0.52
U.K.	0.51	0.55	0.49	0.46	0.43	0.34	0.41	0.61	1.00	0.55
U.S.	0.53	0.57	0.55	0.44	0.38	0.38	0.47	0.62	0.61	1.00

The correlations above the diagonal use returns stated in U.S. dollars, whereas those below the diagonal are the correlations of returns in local currency units. Monthly data covering the period January 1975 to December 2007. Data courtesy of Ken French.

Source: Connor, Goldberg, & Korajczyk (2010).

Macroeconomic risk

- Factor models focus on common components that are pervasive across asset classes, which can often be linked to new information or events that affect a variety of asset classes.
- In many cases, these pervasive shocks can be traced back to realizations or changes in expectations regarding macroeconomic quantities.
- **Event studies** on macroeconomic announcements show strong asset price reactions to these information shocks.
- One key challenge for macro-risk models is that asset prices tend to lead changes in macroeconomic time series.

Macroeconomic risk: Chen et al. (1986)

- Chen, Roll, and Ross (1986, CRR) model equity return as a function of macroeconomic variables.
- They discuss that realized returns are driven by cash flow innovations, new information about future cash flows, and changes in the required returns. These are, in turn, driven by macroeconomic variables.
- They test the following factor model:

$$\begin{aligned} rx_{i,t} &= a + b_{i,MP} MP_t + b_{i,IP} MI_t + b_{i,EI} EI_t + b_{i,UI} UI_t \\ &\quad + b_{i,CG} CG_t + b_{i,GB} GB_t + c_{i,t} \end{aligned}$$

- The factors are mapped to market, industrial production, change in expected inflation, unexpected inflation, change in default risk, and unanticipated change in the term structure.

Macroeconomic risk: CRR – results

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Table 13.4

Economic variables and pricing (percent per month × 10), multivariate approach

A	EWNY	IP	EI	UI	CG	GB	Constant
	5.021	14.009	−0.128	−0.848	0.130	−5.017	6.409
	(1.218)	(3.774)	(−1.666)	(−2.541)	(2.855)	(−1.576)	(1.848)
B	**VWNY**	**IP**	**EI**	**UI**	**CG**	**GB**	**Constant**
	−2.403	11.756	−0.123	−0.795	8.274	−5.905	10.713
	(−0.633)	(3.054)	(−1.600)	(−2.376)	(2.972)	(−1.879)	(2.755)

VWNY = Return on the value-weighted NYSE index; EWNY = Return on the equally weighted NYSE index; IP = Monthly growth rate in industrial production; EI = Change in expected inflation; UI = Unanticipated inflation; CG = Unanticipated change in the risk premium (Baa and under return − Long-term government bond return); GB = Unanticipated change in the term structure (long-term government bond return − Treasury-bill rate); Note that *t*-statistics are in parentheses.

Source: Modified from Nai-Fu Chen, Richard Roll, and Stephen Ross, "Economic Forces and the Stock Market," *Journal of Business* 59 (1986). Reprinted by permission of the publisher, The University of Chicago Press.

Macroeconomic risk: CRR – interpretation

- $\lambda_{IP} > 0$: Stocks more sensitive to production risk are less valuable (therefore have higher returns).
- $\lambda_{CG} > 0$: Stocks more sensitive to the return of low-grade bond returns (relative to that of high-grade bonds) are less valuable ($\rightarrow$ higher exp. returns)..
- $\lambda_{UI} < 0$: Stocks doing well when inflation is unexpectedly high are more valuable ($\rightarrow$ lower exp. returns).

Macroeconomic risk: Campbell and Shiller (1988)

- Consider the unexpected log return $\tilde{r}_t = r_t - \mathbb{E}_{t-1}[r_t]$.
- Using a linear approximation gives an interpretable object,

$$\tilde{r}_t = (\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{j=0}^{\infty} \phi^j (\mathrm{DEX}_{t+j}) - (\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{j=0}^{\infty} \phi^j (r_{t+j}),$$

  - where DEX_{t+j} refers to log dividends (change in expectations about future dividends) and
  - r_{t+j} refers to discount rates (change in expectations about future discount rates.
- A combination of these two components approximately drives unexpected returns.
  - The unexpected return today is high if cash flow expectations have increased or future expected returns have decreased.

Cash flow and discount rate risks

- Does it matter whether stocks fall due to receiving bad news about future cash flows or because the discount rate has increased?
- Campbell and Vuolteenaho (2004) argue: Yes.
  - In the first case, wealth decreases and investment opportunities are unchanged.
  - In the second case, wealth decreases but future investment opportunities improve.
- Measuring cash-flow and discount-rate betas is useful as the corresponding risk premia differ.

FX risk

- Foreign exchange risk arises from the volatility of exchange rates. Investments in foreign currency fluctuate when the exchange rate moves.
- In practice, the optimal allocation to foreign currencies is typically not part of the portfolio optimization but managed in a second step, after risky positions in assets have been determined.
- For a Euro investor, the return from an investment in dollar-denominated assets is

$$R^{€}_{\text{SPX}} = (1 + R^{\$}_{\text{SPX}})(1 + R^{€/\$}) - 1$$

- or, using log returns,

$$r^{€}_{\text{SPX}} = r^{\$}_{\text{SPX}} + r^{€/\$}$$

FX risk (ii)

- The variance-minimizing hedge ratio is obtained from a regression of asset returns in € (HC) on the exchange rate,

$$h^* = \frac{\sigma_{spx^{€},€/\$}}{\sigma^2_{€/\$}}$$

- Common variants:
  - $h^* = 0$: no hedge if the stock return (measured in HC) and the exchange rate are uncorrelated
  - $0 < h^* < 1$: partial hedge if covariance is positive but not large
  - $h^* = 1$: full hedge if covariance equals FX variance.
- Usually not feasible are these variants:
  - $h^* =< 0$: take additional USD exposure when FX movements offset equity losses
  - $h^* > 1$: overhedge, when covariance is very high
- To hedge, take the offsetting position $-h^*$.

FX risk (iii)

- The variance-minimizing hedge typically leads to hedge bonds fully and keep stocks mostly unhedged.
- In practice, bond hedge funds do not follow this advice.
- The reason is that beyond the variance-minimizing hedge, they take into account expected currency returns.
- For example, the forward discount is a predictor of currency returns. Thus, it makes sense to hedge exposure to low-interest currencies to a higher degree, and exposure to high-interest currencies to a lesser degree.
- When dealing with currencies, be aware of the **peso problem**. An OLS regression might not reveal the true exposure.

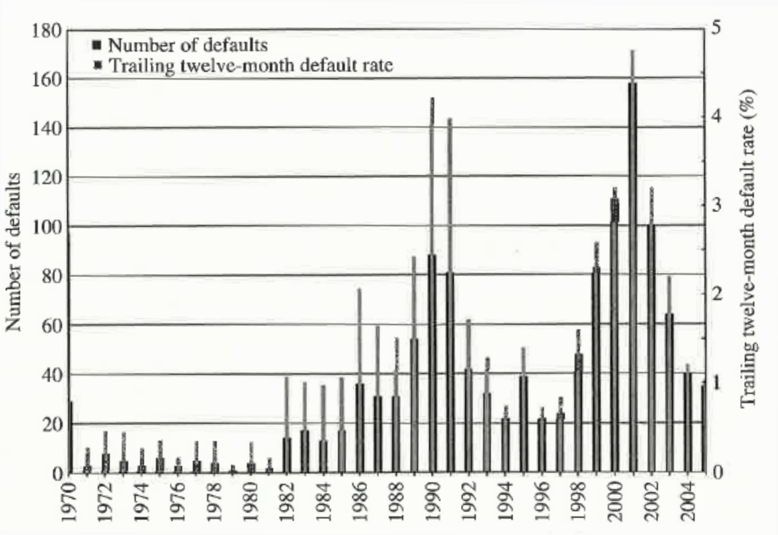
Example

- Consider the data provided for the S&P 500 and the €/$ exchange rate.
- Estimate the optimal (variance minimizing) hedge ratio.
- State (in-sample) volatilities of the stock market in local (=foreign) currency and in €, the exchange rate, and of the optimally hedged position.

Credit risk

- Credit risk refers to the uncertainty about whether a counterparty will honor a financial obligation.
- **Credit ratings** for specific issues or issuers are a key metric for assessing credit risk.
- However, credit ratings are not constant, making **transition** models insightful (see, e.g., Jarrow et al., 1997).
- Intuition provided by **structural models** of Merton (1974) and Vasicek (2002) resulted in **physical default probabilities** from Moody's KMV model.
- We will cover this in detail in ARM2.

Example credit risk

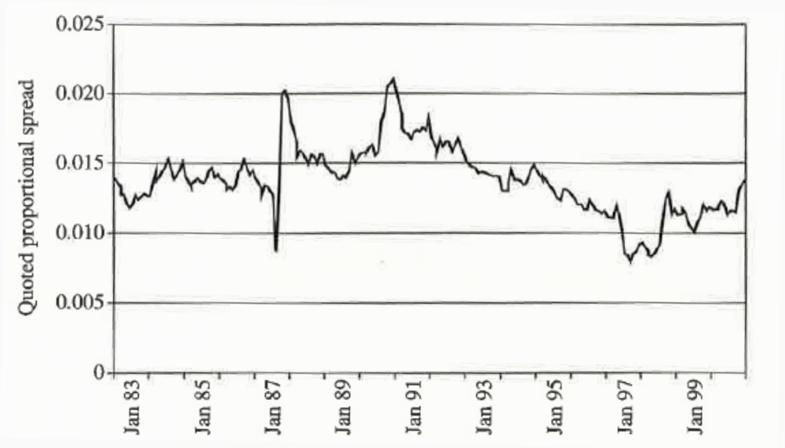


Source: Connor, Goldberg, & Korajczyk (2010).

Transaction costs and liquidity risk

- **Transaction costs** are a critical component of portfolio risk analysis (and asset management more generally).
  - Transaction costs are usually measured as the (proportional) bid-ask spread, but numerous other measures exist (e.g., Roll, Amihud, price dispersion).
- **Liquidity risk** refers to the uncertainty connected to the ability to liquidate a portfolio at a “fair price”.
  - Liquidity is known to be rather stable until it jumps significantly following certain events (e.g., LTCM crash).
  - However, liquidity freezes are less common in equity markets than in many other markets.
- Additionally, transaction costs and the associated liquidity risk are sensitive topics in times when other risks materialize.

Example transaction costs



Source: Connor, Goldberg, & Korajczyk (2010). Average for stocks traded on the NYSE from 01/1983-12/2000.

Operational risk

- Jorion (2007) defines **operational risk** as “inadequate systems, management failure, faulty controls, fraud, or human error”.
  - In practical applications, systems for measuring and controlling operational risk are extremely important.
  - Legal and regulatory concerns play a large role.
- Additionally, **model risk** can arise due to misspecification or estimation error in the risk analysis tools.
- Risk management is about more than calibration and application of ever fancier models.

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