Managing Risks in a Risk-On/Risk-Off Environment

Marcos López de Prado

Lawrence Berkeley National Laboratory

Computational Research Division





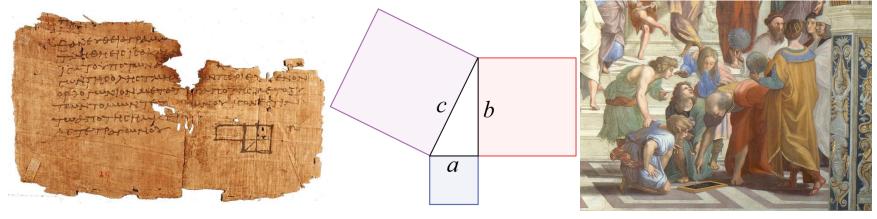
Key Points

- Every structure has <u>natural frequencies</u>. Minor shocks in these frequencies can bring down any structure, e.g. <u>a bridge</u>.
- Your investment universe also has natural frequencies, characterized by its eigenvectors.
- A concentration of risks in the direction of any such eigenvector exposes a portfolio to the possibility of greater than expected losses (indeed, maximum risk for that portfolio size), even if that portfolio is below the risk limits.
- This is particularly dangerous in a risk-on/risk-off regime.
- Managing Risk is not only about limiting its amount, but also controlling how this amount is concentrated around the natural frequencies of the investment universe.

SECTION I The Geometry of Risk and Correlation

Pythagoras' Theorem and the Law of Cosines

• Pythagoras (570-495 BC) is credited with proving that, "in a right triangle, the square of the hypotenuse equals the sum of the squares of the catheti". [This proposition has received at least 370 different proofs ever since, and even inspired several cults!]



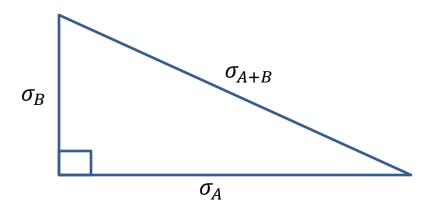
• When there is no right angle, the **Law of Cosines** states that: $a^2 + b^2 - 2ab \cos \theta = c^2$

The Geometry of Risk (1/3)

- Suppose that you hold two uncorrelated assets:
 - One unit of A, with standard deviation of returns $\sigma(A) = a$.
 - One unit of B, with standard deviation of returns $\sigma(B) = b$.
- The standard deviation of your holdings' returns is

$$\sigma_{A+B} = \sqrt{\sigma_A^2 + \sigma_B^2} = c$$

This reminds us of Pythagoras' theorem.

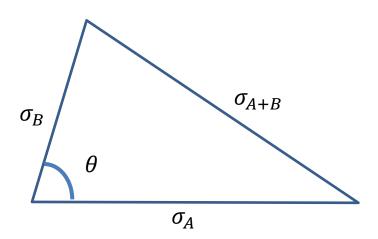


The Geometry of Risk (2/3)

- What if A and B are correlated $(\rho_{A,B} \neq 0)$?
- Then, the standard deviation of your holdings' returns is

$$\sigma_{A+B} = \sqrt{\sigma_A^2 + \sigma_B^2 + 2\sigma_A\sigma_B\rho_{A,B}}$$

Again, this has a geometric analogue in the law of cosines.

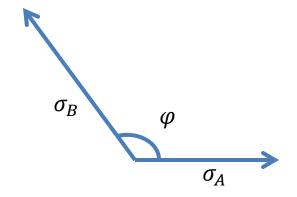


The Geometry of Risk (3/3)

 Conclusion 1: Correlation can be understood geometrically as the negative of the cosine of the angle between the two vectors representing A and B.

$$ho_{A,B}=-cos heta$$

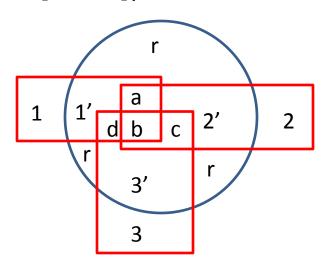
• Or equivalently, for $\varphi = \pi - \theta$,



$$\rho_{A,B} = \cos\varphi = \frac{\langle A,B \rangle}{\|A\| \|B\|} = \frac{\sigma^2_{A,B}}{\sigma_A \sigma_B}$$

Average Correlation and Regressions

- Correlations are useful to measure levels of risk.
- Correlations are defined in pairs, and fail to capture complex relations in spaces of dimension beyond 2.
- <u>Conclusion 2</u>: Average/implied correlation cannot measure concentration of risk (e.g., Kritzman et al. [2010]).



Regressions also fail to evaluate concentration, because they:

- translate risk in terms of a list of correlated securities (1, 2, 3, with overlapping variance).
- leave an unexplained residual (r), which may hide risk concentration.

The problem with correlated assets

• In an ideal world, we would like to work with uncorrelated assets $(Z_1, Z_2, Z_3,...)$, because in that ideal world we could compute risk by simple addition, without informational loss, like in **Pythagoras' theorem**:

$$\sigma_{Z_1 + Z_2 + Z_3 + \dots} = \sqrt{\sigma_{Z_1}^2 + \sigma_{Z_2}^2 + \sigma_{Z_3}^2 + \dots}$$

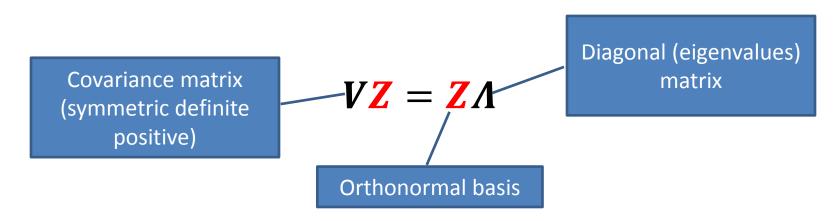
.... instead of being forced to apply the law of cosines.

Investment Universes are not "Pythagorean"...
 What can we do?

SECTION II Eigen-decomposition of Risk

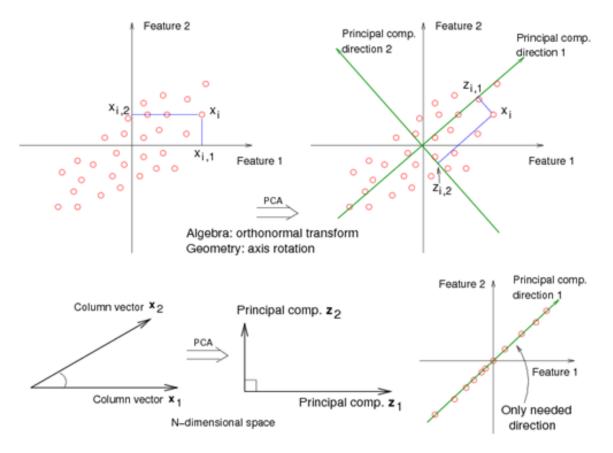
Living in an "orthogonal" (investment) Universe

- If we don't like the investment Universe we live in, Linear Algebra can "move" us to another one of our liking...
- Eigenvector's key idea: Compute linear combinations of correlated assets that result into uncorrelated subportfolios.



Why does this work? (Intuitively)

 This sounds like magic, but it is an application of the "Spectral Theorem".



Conclusion 3: We can express any observation (x_i) in a new coordinate system (given by V's eigenvectors) such that its components $(z_{i,1}, z_{i,2})$ are orthogonal to each other.

Why does this work? (The Spectral Theorem)

Because a covariance matrix V is squared and symmetric, its eigenvector decomposition delivers a set of real valued orthonormal vectors, such that

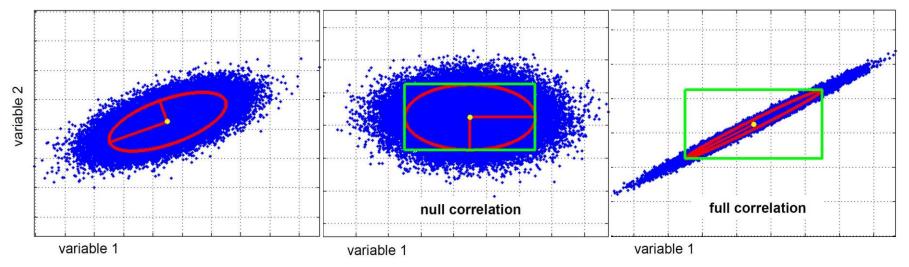
$$V = \mathbf{Z} \mathbf{\Lambda} \mathbf{Z}^T$$

where Λ is the eigenvalues matrix, \mathbf{Z} is the eigenvectors matrix, and \mathbf{Z}^T denotes its transpose. Λ is a diagonal matrix and the columns of \mathbf{Z} are orthogonal to each other, i.e. $\mathbf{Z}^T = \mathbf{Z}^{-1}$. For convenience, we reorder columns in \mathbf{Z} and Λ so that $\Lambda_{i,i} \geq \Lambda_{j,j}$, $\forall j > i$. The i-th principal component is defined by a portfolio with the holdings listed in the i-th column of \mathbf{Z} .

Looking at the above equation, Λ can then be interpreted as the covariance matrix between the principal components characterized by the columns of \mathbf{Z} . The factor loadings vector $\mathbf{f}_{\omega} = \mathbf{Z}^T \boldsymbol{\omega}$ gives us the projection of a vector of holdings $\boldsymbol{\omega}$ into this new orthogonal basis \mathbf{Z} . This can be verified from $\sigma^2 = \boldsymbol{\omega}^T V \boldsymbol{\omega} = \boldsymbol{\omega}' \mathbf{Z} \Lambda \mathbf{Z}^T \boldsymbol{\omega} = \mathbf{f}_{\omega}' \Lambda \mathbf{f}_{\omega}$. The product $\mathbf{f}_I = \mathbf{Z}' \mathbf{I}$, where \mathbf{I} represents the identity matrix, gives us the directions of the old axes in the new basis. See Bailey and López de Prado (2012) for additional details and examples.

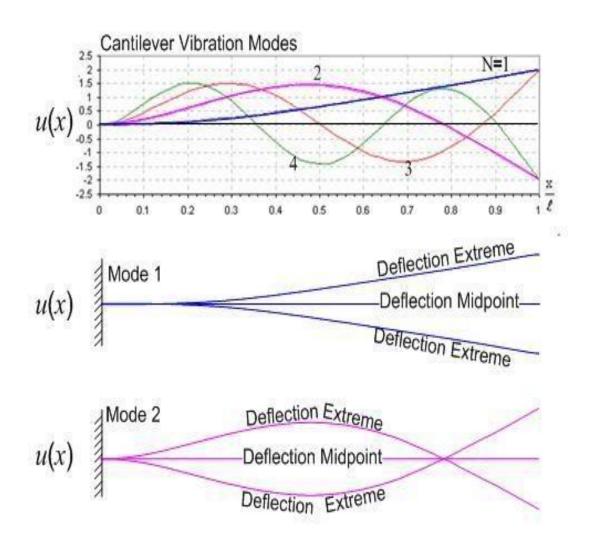
The dispersion ellipsoid

 When two assets A and B are correlated, the scatter plot of returns is contained by a rotated ellipsoid (left chart) with a given probability. [note on elliptical dists. and Chebyshev's boundary]



 The more correlated A and B are, the more rotated and collapsed the ellipsoid is towards a single direction (i.e., there is only one true bet). See Meucci (2005).

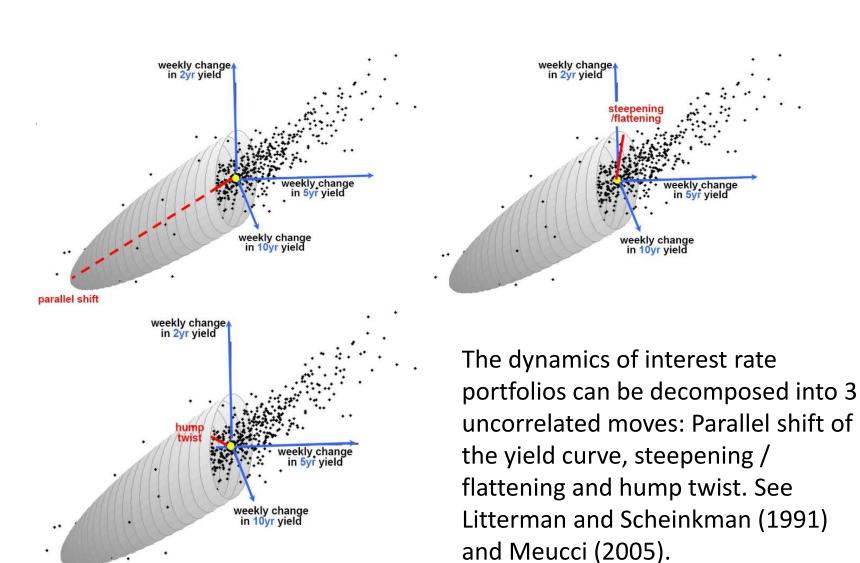
Examples of Eigen-Analyses (1/2)



Consider a plank fixed to a wall, with three weights attached to it at equidistant intervals.

This cantilever can only vibrate at 3 "natural frequencies" or "vibration modes", i.e. any vibration is simply a linear combination of these modes.

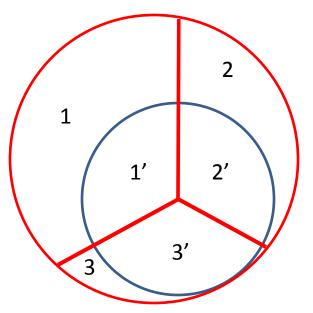
Examples of Eigen-Analyses (2/2)



SECTION III Eigenvectors as pure bets

Thinking in terms of pure bets (1/2)

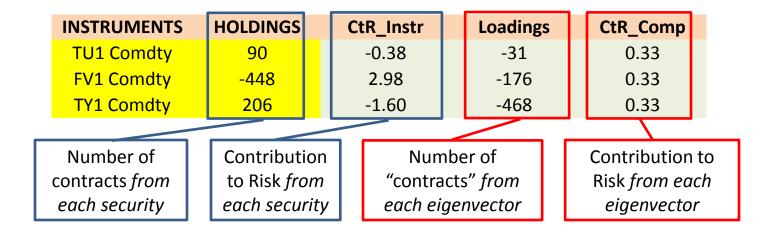
- Eigenvectors form a new basis.
- They are mutually uncorrelated, and explain the full variance of the investment universe, without overlaps.

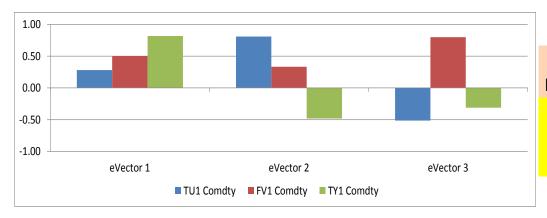


- Eigenvectors define the pure bets offered by the investment universe.
- Your portfolio can be translated in terms of combinations of those pure bets.
- Example: The figure to the left shows how a portfolio (in blue) receives equal risk contribution from every bet in the investment universe (red).
- There is no overlap or residual [compare with slide 8!].

Thinking in terms of pure bets (2/2)

 Example: A fixed income portfolio with holdings in 2y, 5y and 10y U.S. Treasury Note Futures.

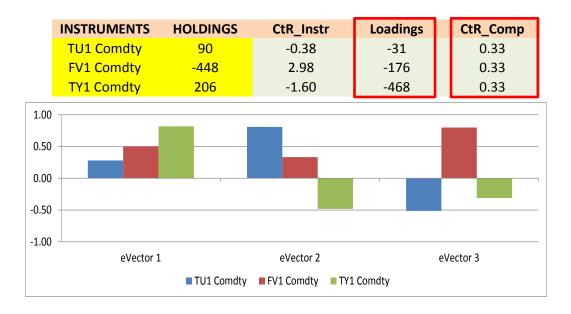




eValues	315699	9569	1347
INSTRUMENTS	eVector 1	eVector 2	eVector 3
TU1 Comdty	0.28	0.81	-0.51
FV1 Comdty	0.50	0.33	0.80
TY1 Comdty	0.82	-0.48	-0.31

Uncorrelated bets

- Going back to the previous example, the Contribution to Risk in terms of the original instruments gave the (false) impression of a huge concentration around FV1 Comdty.
- <u>Conclusion 4</u>: "Loadings" express the portfolio holdings in terms of uncorrelated sub-portfolios (the Eigenvectors).



In terms of Risk contributed by each component, 1/3 comes from the 1st eigenvector (market component), 1/3 from the 2nd eigenvector (steepness component), and 1/3 from the 3rd eigenvector (convexity component).

SECTION IV Eigenvectors and Risk-On/Risk-Off

Beware of "holding" an eigenvector (1/3)

- Holding an eigenvector means that the entire risk has been allocated to a single bet, e.g. $\omega = Z_1$.
- The problem is, if a *structural break* occurs, and as a result the realized risk is greater than expected $(\Lambda_{1,1})$, V will not be able to dissipate the hit.
- Remember: An eigenvector makes the covariance matrix behave like a simple scalar...

$$VZ_1 = \lambda_1 Z_1$$

... and what is worse, the portfolio can really blow-up!

$$\boldsymbol{V}^{m}\boldsymbol{Z}_{1}=\lambda_{1}^{m}\boldsymbol{Z}_{1}$$

Beware of "holding" an eigenvector (2/3)

Bailey and López de Prado (2012) show that

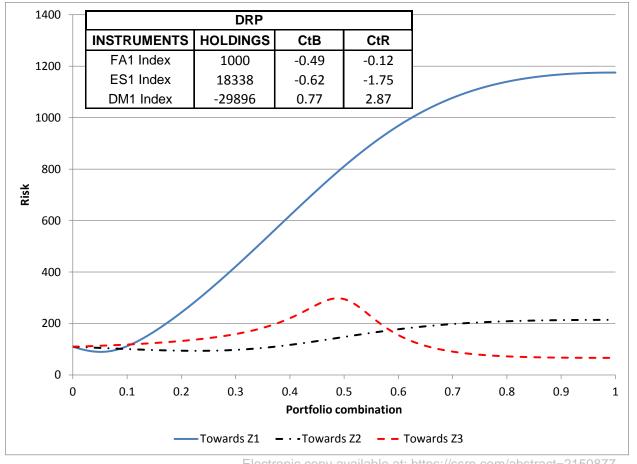
"risk increases as we approach a basket pointing in the direction of an eigenvector, except in the case of the eigenvector associated with the lowest eigenvalue. This is because eigenvectors are the critical points of the Rayleigh quotient

$$R[\boldsymbol{\omega}, \boldsymbol{V}] = \frac{\boldsymbol{\omega}' \boldsymbol{V} \boldsymbol{\omega}}{\boldsymbol{\omega}' \boldsymbol{\omega}}$$

where the numerator is the variance of the basket".

Beware of "holding" an eigenvector (3/3)

 If the risk contributed by every eigenvector direction is the same, that portfolio is called DRP.

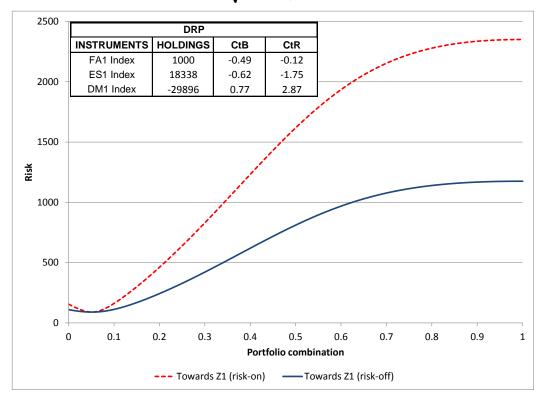


Conclusion 5:

Risk raises as we move away from DRP and towards the eigenvectors 1 and 2. Eigenvectors are the portfolios Z_i that maximize $Z_i'VZ_i$ (and therefore risk) for that portfolio size, $Z_i'Z_i$.

Risk-On/Risk-Off

• Below is the risk of a portfolio that moves towards Z_1 , before (risk-off) and after (risk-on) a 100% increase in $\sqrt{\Lambda_{1,1}}$.



Investors holding the first eigenvector receive the entirety of the shock, and their risk is doubled. That shock would have been greatly dissipated by the investment universe if the investor had held a larger number of pure bets, instead of being so exposed to the first eigenvector.

The Tacoma Narrows Bridge disaster

- On July 1st 1940, the Tacoma Narrows Bridge opened to traffic. It collapsed @ 11:10am of November 7th 1940, when a mild gale (40 mph) blew in the direction of one of the bridge's eigenvectors.
- Unable to dissipate that force, aeroelastic flutter occurred.

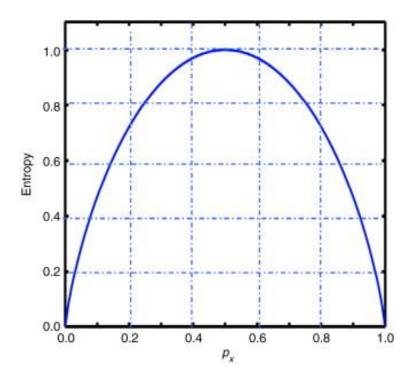


Like the <u>Tacoma</u>
Narrows Bridge, your investment universe is unable to re-distribute the extra load hitting from an eigenvector's direction.

SECTION V Risk Level vs. Risk Concentration

What is Entropy?

- Entropy is a concept borrowed from Information Theory. It measures the uncertainty of a random variable.
- For example, suppose that you toss a coin:



- 1. If the coin is fair, there is maximum entropy (minimum certainty) with regards to the outcome.
- 2. If the coin has two heads $(p_x = 1)$ or two tails $(p_x = 0)$, there is minimum entropy (maximum certainty).
- 3. If the coin is biased, Entropy has an intermediate value.

What is Portfolio Entropy?

- <u>Conclusion 6</u>: We can measure concentration in terms of how unevenly risk is contributed by the various eigenvectors that characterize the investment universe.
- The Contribution to Risk by the *i*-th eigenvector is

$$\widetilde{CtR_i} = \frac{[f_{\omega}]_i^2 \Lambda_{i,i}}{\sum_{j=1}^n [f_{\omega}]_j^2 \Lambda_{j,j}}$$

• Then, Portfolio Entropy can be defined as (Meucci (2010))

$$H_{Ent} \equiv \frac{exp(-\sum_{i=1}^{n} \widetilde{CtR_i} Ln(\widetilde{CtR_i})) - 1}{n-1}$$

 Entropy ranges between 0 (max. concentration) and 1 (max. diversification).

Concentration is defined in "relative" terms

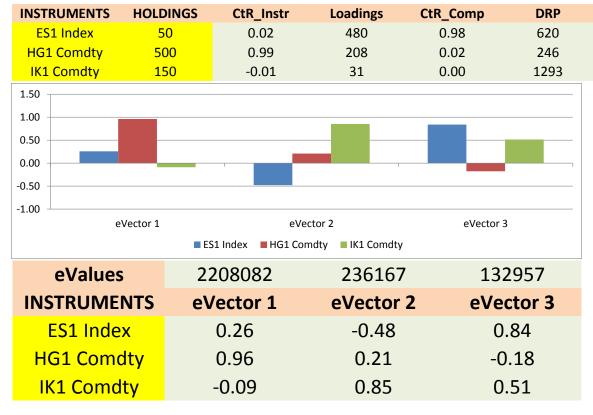
- Each investment universe determines different pure bets.
- Entropy assesses a portfolio's concentration relative to its exposure to those pure bets.
- <u>Conclusion 7</u>: A portfolio is concentrated or diversified only relative to the pure bets in that investment universe.
- Consider a PM who can only invest in U.S. rates, while a second PM in U.S. rates and EUR/USD. If they have the same portfolio, then the latter is surely more concentrated.

INSTRUMENTS	HOLDINGS	CtR_Instr	Loadings	CtR_Comp	DRP	Entropy
TU1 Comdty	-90	-0.38	31	0.33	-90	1.00
FV1 Comdty	449	2.98	176	0.33	449	Imp. Correl
TY1 Comdty	-206	-1.60	469	0.33	-206	0.98
INSTRUMENTS	HOLDINGS	CtR_Instr	Loadings	CtR_Comp	DRP	Entropy
TU1 Comdty	-90	-0.38	-5	0.03	-79	0.76
FV1 Comdty	449	2.98	30	0.31	389	Imp. Correl
TY1 Comdty	-206	-1.60	176	0.33	-180	0.98
EC1 Curncy	0	0.00	469	0.33	19	

SECTION VI Practical Examples

Example I: Concentration with Low Correlation

 Portfolio combining Futures on E-Mini S&P 500, Euro-BTP Italian Govt Bonds and Copper.



98% of the risk comes in the direction of the first eigenvector. The portfolio's Entropy is only 0.05, signaling a large concentration, and yet the implied correlation is 0. At least the CtR (in terms of instruments) was able to pick a problem related to to copper.

Entropy

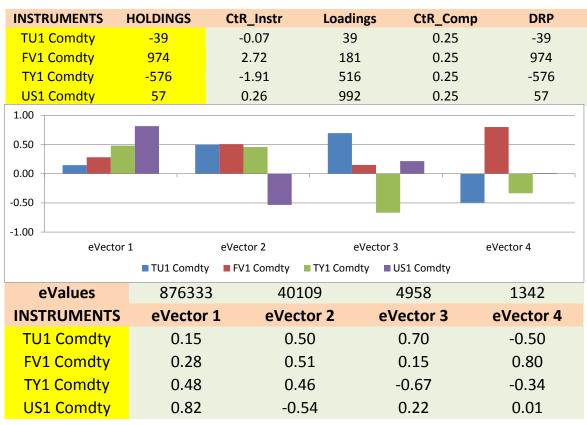
0.05

Imp. Correl

0.00

Example II: Diversification with High Correlation

Portfolio combining Futures on U.S. Treasury Notes.



Risk is evenly split between the four pure bets (a DRP portfolio). Portfolio's Entropy is 1, signaling total diversification given that investment universe. However, implied correlation is 0.98. CtR (in terms of instruments) also fails to recognize diversification.

Entropy

1.00

Imp. Correl

0.98

How can I diversify my portfolio?

- Option 1: Increase your exposure to an eigenvector that is not contributing risk.
- Option 2: Decrease your exposure to the eigenvector that is contributing most of the risk.
- Example I exhibited a large concentration of risks in the direction of the first eigenvector. We can reduce that concentration by blending that portfolio with a "balanced basket", such as DRP (e.g., a 50% blend).

INSTRUMENTS	HOLDINGS	CtR_Instr	Loadings	CtR_Comp	DRP	Entropy
ES1 Index	307	0.17	380	0.74	565	0.56
HG1 Comdty	362	0.71	532	0.15	224	Imp. Correl
IK1 Comdty	664	0.12	586	0.11	1179	-0.01

SECTION VII Balanced Baskets and Risk Diversification: An Introduction

What is a "balanced basket"?

- A basket is a set of instruments that are held together because its statistical profile delivers a desired goal (such as hedging or trading), which cannot be achieved through the individual constituents or even subsets of them.
- "Balanced baskets" distribute risk or exposure across their constituents without requiring a change of basis.
- Practitioners typically prefer "balanced baskets" because their output can be understood in the same terms for which they have developed an intuition.

Equal Risk Contribution, alias "Risk Parity" (ERC)

- Demey, Maillard and Roncalli (2010).
- ERC is the basket that equalizes the contribution to risk from each constituent.

$$\omega_{ERC} = \left\{ \omega_i \left| \frac{\sigma_{\Delta B, \Delta S_i}}{\sigma_{\Delta B}^2} = \frac{1}{n}, \forall i \right\} \right\}$$

 Despite its popularity, ERC presents a number of inconveniences. Like correlations and regressions, it doesn't take into account the deep geometry of the investment Universe. For example:

INSTRUMENTS	HOLDINGS	CtR_Instr	Loadings	CtR_Comp	DRP	Entropy
ES1 Index	1530	0.33	734	0.15	-5567	0.27
DM1 Index	1760	0.33	3718	0.85	9793	Imp. Correl
TY1 Comdty	3000	0.33	272	0.00	1249	-0.20

Maximum Diversification Ratio (MDR)

- Choueifaty and Coignard (2008).
- MDR is the basket that maximizes the diversification ratio:

$$\omega_{MDR} = \arg\max_{\omega} \quad \frac{\sum_{i=1}^{n} \omega_{i} \sigma_{i}}{\sigma_{\Delta B}}$$

- MDR is an intuitive method that penalizes the risk associated with cross-correlations, as they are accounted by the denominator but absent in the numerator of the maximized ratio.
- However, like ERC, it fails to control for the exposure of the basket to subsets of constituents.

Diversified Risk Parity (DRP)

- Defined by Lohre, Neugebauer and Zimmer (2012).
- Analytical solution by <u>Bailey and López de Prado</u> (2012).
- DRP is the basket such that risk is equally distributed among all pure bets (Entropy is set to 1).

$$\omega_{DRP} = \left\{ W f_{\omega} \middle| [f_{\omega}]_i = \sqrt{\frac{\Lambda_{1,1}}{\Lambda_{i,i}}}, \forall i \right\}$$

 Not strictly a "balanced basket", as a change of basis is still required.

Mini-Max Subset Correlation (MMSC)

- López de Prado and Leinweber (2012).
- MMSC is the solution that minimizes the correlation of the basket to any leg or subset of legs.

$$\omega_{MMSC} = \arg\min_{\omega} \left\{ \max_{i} |\rho_{\Delta B, \Delta S_i}| \right\}$$

- This is the closer to Spectral decomposition, without requiring a change of basis.
- Beyond Hedging Baskets, MMSC can also be used for Trading Baskets, i.e. to acquire risk or exposure to each and every of its legs (or subsets of them) in a balanced way: $\omega_{MMSC} = \arg \max \{\min |\rho_{\Delta B, \Delta S_i}|\}$

$$\{\min_{i} | \rho_{\Delta B, \Delta S_i} | \}$$

SECTION VIII Conclusions

Conclusions (1/2)

- 1. Correlations are a function of the angle between two vectors [law of cosines]. This causes problems in portfolios of more than two holdings.
- 2. Correlations and regression analysis can measure *risk levels*, however they fail to measure *risk concentration*.
- 3. The Spectral theorem allows us to move into a space of uncorrelated sub-portfolios (eigenvectors) [what we needed to apply Pythagoras' theorem!].
- 4. Our portfolio can then be expressed as "loadings", i.e. pure bets on our investment universe.

Conclusions (2/2)

- 5. The problem with *concentrating risk* on an eigenvector (except for the last one) is that it maximizes the risk for that portfolio size (**Rayleigh quotient**). This is rather dangerous in a Risk-on / Risk-off environment!
- 6. We can measure and monitor risk concentration in terms of a portfolio's **Entropy**: How unevenly risk is contributed by the various eigenvectors that characterize the investment universe.
- 7. Concentration can only be understood in relative terms to the investment universe's pure bets.

Food for thought

- Keeping the risk level under control is not enough in a risk-on/risk-off regime like the current.
- Equally important is to monitor risk concentration.
- Correlation and regression analysis measure risk levels, however fail to monitor for risk concentration.
- **Portfolio entropy** is an adequate measure of risk concentration.
- Balance baskets diversify risk without requiring a change of basis. It is the closest we can get to Pythagoras without using the Spectral theorem.

THANKS FOR YOUR ATTENTION!

SECTION IX The stuff nobody reads

Bibliography

- Bailey, D. and M. López de Prado (2012): "Balanced Hedging and Trading Baskets", Journal of Investment Strategies, Vol.1(4), Fall: http://ssrn.com/abstract=2066170.
- Choueifaty, Y. and Y. Coignard (2008): "Toward Maximum Diversification", The Journal of Portfolio Management, 34(4), pp. 40-51.
- Demey, P., S. Maillard and T. Roncalli (2010): "Risk-based indexation", SSRN, working paper.
- Jennings, A. and J. McKeown (1992): "Matrix computation", Wiley.
- Kritzman, M., Y. Li, S. Page, R. Rigobón (2010): "Principal Components as a Measure of Systemic Risk", MIT Sloan School Working Paper 4785-10.
- Litterman, R. and J. Scheinkman (1991): "Common Factors Affecting Bond Returns", Journal of Fixed Income, June.
- Lohre, H., U. Neugebauer and C. Zimmer (2012): "Diversifying Risk Parity", SSRN.
- López de Prado, M. and D. Leinweber (2012): "Advances in Cointegration and Subset Correlation Hedging Methods", Journal of Investment Strategies, Vol.1(2), Spring, pp.67-115. http://ssrn.com/abstract=1906489.
- Meucci, A. (2005): "Risk and Asset Allocation", Springer. http://symmys.com/attilio-meucci/book
- Meucci, A. (2010): "Managing Diversification", Risk (April), pp. 74-79.
 http://www.symmys.com/node/199

Bio

Marcos López de Prado is Senior Managing Director at Guggenheim Partners. He is also a Research Affiliate at Lawrence Berkeley National Laboratory's Computational Research Division (U.S. Department of Energy's Office of Science).

Before that, Marcos was Head of Quantitative Trading & Research at Hess Energy Trading Company (the trading arm of Hess Corporation, a Fortune 100 company) and Head of Global Quantitative Research at Tudor Investment Corporation. In addition to his 15+ years of trading and investment management experience at some of the largest corporations, he has received several academic appointments, including Postdoctoral Research Fellow of RCC at Harvard University and Visiting Scholar at Cornell University. Marcos earned a Ph.D. in Financial Economics (2003), a second Ph.D. in Mathematical Finance (2011) from Complutense University, is a recipient of the National Award for Excellence in Academic Performance by the Government of Spain (National Valedictorian, 1998) among other awards, and was admitted into American Mensa with a perfect test score.

Marcos is the co-inventor of four international patent applications on High Frequency Trading. He has collaborated with ~30 leading academics, resulting in some of the most read papers in Finance (SSRN), three textbooks, publications in the top Mathematical Finance journals, etc. Marcos has an Erdös #3 and an Einstein #4 according to the American Mathematical Society.

Notice:

The research contained in this presentation is the result of a continuing collaboration with

Prof. David H. Bailey, LBNL

The full paper is available at:

http://ssrn.com/abstract=2066170

For additional details, please visit:

http://ssrn.com/author=434076 www.QuantResearch.info

Disclaimer

- The views expressed in this document are the authors' and do not necessarily reflect those of the organizations he is affiliated with.
- No investment decision or particular course of action is recommended by this presentation.
- All Rights Reserved.