Using Python to Quantify Portfolio Diversification

Robin Warner

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THANK YOU DOUG & TEAGAN

Agenda

- I. Background Theory
- II. Data Set & Problem Space
- III. Diversification Metrics
- IV. Applications & Resources

I. Background Theory

What is an Investment?

An asset or item acquired with the goal of generating a profit over a given timeframe.

What is an Investment?

Use today's expectations of tomorrow

Invest Today

Generate Profit

Accumulate gain or loss

• Redeem the investment

Consume Tomorrow

What is required to invest?

Expectations of the future (and the potential rewards available)

What is required to invest?

More specifically,

Expectations of future <u>changes</u> in the value of an investment (i.e. the investment's **Expected Return**)

So what's the problem?

The future is uncertain.

So what's the problem?

Expected Returns ≠ Realized Returns

So, what is required to invest (again)?

Expectations of the future (i.e. the investment's **Expected Return**)

...and a measure of how wrong we may be about the future (i.e. the investment's **Risk**)

How to estimate an investment's characteristics

Expected Return = $\mathbf{E}(\mathbf{R}_i)$

Historical Average

DCF Model

Earnings Multiple

Macro Economic Model

Risk = σ_i

Historical Volatility

Historical Variance

Historical Inter-quartile Range



How to measure an investment's characteristics

Expected Return = $\mathbf{E}(\mathbf{R_i})$

Historical Average

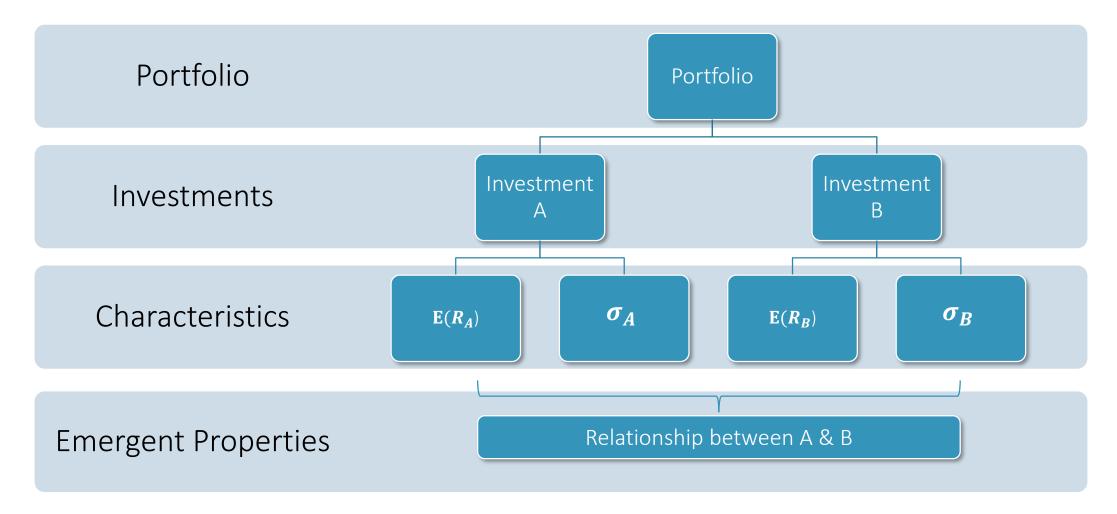
• 5 yr avg monthly return

Risk =
$$\sigma_i$$

Historical Volatility

• 5 yr avg monthly dispersion around the historical average

What is a Portfolio?



What is a Portfolio's Expected Return?

The Expected Return of a Portfolio:

$$\mathbf{E}(R_{pf}) = \sum_{i} w_{i} \mathbf{E}(R_{i})$$

Where:

 $\mathbf{E}(R_{pf})$ – The expected return of the portfolio, \mathbf{w}_i – The weights of each investment within the portfolio, and $\mathbf{E}(R_i)$ – The expected return of each investment within the portfolio.

What is Portfolio Risk?

The Volatility of a Portfolio:

$$\sigma_{pf} = \sqrt{\sum_{i} w_{i}^{2} \sigma_{i}^{2} + \sum_{i} \sum_{j \neq i} w_{i} w_{j} \sigma_{i} \sigma_{j} \rho_{ij}}$$

Where:

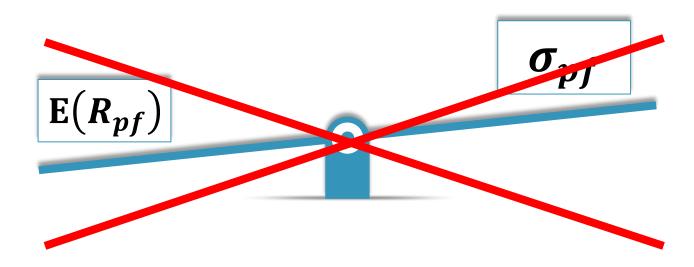
 σ_{pf} – the volatility of the portfolio,

 $\boldsymbol{w_i}$, $\boldsymbol{w_i}$ -the weights of investments *i* and *j* respectively within the portfolio,

 σ_i , σ_i – the volatilities of investments i and j respectively within the portfolio, and

 ρ_{ij} – the correlation between investments i's and j's returns

How to manage both Risk & Reward?



Through Portfolio Efficiency

Portfolio Efficiency

A measure of how much reward a portfolio may produce for every unit of risk taken

Portfolio Efficiency

Risk Adjusted
$$E(R_{pf}) = E(R_{pf})/\sigma_{pf}$$

What is Portfolio Diversification?

Diversification is a <u>risk</u> management technique that aims to minimize the impact of any single investment's performance on that of the total <u>portfolio</u>.

Portfolio Efficiency & Diversification

How can one use diversification to achieve an efficient portfolio?

II. Data Set & Problem Space

Pandas & the Pandas DataFrame

What is Pandas?

- Popular Python library used for data manipulation and analysis
- Developed by Wes McKinney in the late 2000s
- Name derived from the term "panel data"
- Primary data structure known as the **DataFrame** object

Why use the DataFrame Object?

- Easy to use table object
- Lots of built in functionality including missing data handling, charting, statistics, & hierarchical labeling
- Similar to R's data.frame object

The Data

The Standard & Poor's 500 Index (i.e. S&P 500):

American stock market index

500 largest companies by market capitalization listed on the NYSE or NASDAQ

More or less market cap weighted

Rich historical data available

DATE	AFL.N	AES.N	ABT.N	ABMD.OQ	ATVI.OQ	ADBE.OQ	AMD.OQ	AMG.N	APD.N	ALK.N	ALB.N	ALXN.OQ	HON.N	ALL.N	ARNC.N	HES.N	AEE.N	AEP.N	AXP.N	AIG.N	ABC.N	AME.N A
2013-01-31	-0.00113				072505	0.003981	0.083333	0.105878	0.040551	0.070534	-0.01304	0.001919	0.075107	0.092855	0.018443	0.268127	0.05599	0.061153	0.023138	0.071671	0.050718	0.09103
2013-02-28	-0.05842	0.07	⁻ 500 S	Stocks	255487	0.038858	-0.04231	0.01598	-0.0125	0.117469	0.061491	-0.07714	0.027266	0.048292	-0.03622	-0.00983	0.041615	0.03312	0.056793	0.004758	0.040335	0.020493
2013-03-31	0.041233					0.107123	0.024050	0.030133	0.00502	0.240437	-0.05554	0.002233	0.074032	0.000270	U	0.070042	0.030401	0.033323	0.000400	.02131	0.090042	0.036577
2013-04-30	0.046521	0.10	Colu	mns	026081	0.036084	0.105882	0.01374	-0.00186	-0.03627	-0.02031	0.063599	-0.02403	0.003872	-0.00209	0.00796	0.035123	0.057578	0.014082	0.066976	0.051895	-0.06112
2013-05-31	0.023145	-0.1			.03478	-0.04814	0.41844	0.053443	0.085707	-0.0782	0.092571	-0.00469	0.066876	-0.02071	0	-0.06608	-0.06097	-0.10908	0.10671	0.073394	-0.00074	0.059936
2012 05 20	0.040447	0.0172	1 -0.04881	-0.00046	-0.01178	0.061757	0.02	-0.00037	-0.03002	-0.08483	-0.06919	-0.05434	0.011281	-0.00249	-0.08002	-0.01365	0.011751	-0.0227	-0.01255	0.005398	0.032359	-0.0197
4 60) Date	<u>3</u>	1 0.050172	0.163265	0.26087	0.037752	-0.07598	0.100098	0.186393	0.176538	-0.0045	0.260082	0.045887	0.059435	0.016487	0.119868	0.039779	0.03506	-0.01324	0.018121	0.043704	0.09409
2	2		4 -0.09009	-0.061	-0.09232	-0.03236	-0.13263	-0.03343	-0.05984	-0.07453	0.005806	-0.07287	-0.04109	-0.06002	-0.03132	0.005238	-0.05585	-0.07659	-0.02521	0.020875	-0.02317	-0.0726
2 F	Rows	33	3 -0.0042	-0.19023	0.021446	0.135301	0.16208	0.047728	0.043313	0.10597	0.009139	0.077951	0.043605	0.054883	0.054273	0.033267	0.030464	0.01285	0.050202	0.046707	0.073436	0.072227
11)÷	6 0.101235	0.257472	-0.0018	0.043512	-0.12105	0.081034	0.02294	0.128393	0.051636	0.058454	0.044447	0.049654	0.14184	0.049909	0.038462	0.080507	0.083157	0.062102	0.069231	0.039331
2013-11-30	0)21545	0.03406	7 0.04487	0.192244	0.034255	0.047601	0.08982	0.014232	-0.00169	0.100198	0.038072	0.012607	0.020524	0.022804	0.036451	-0.00086	-0.00912	0.004697	0.0489	-0.03679	0.079596	0.029061
2013-12-31	0 006327	-0.00412	2 0.003666	-0.06471	0.036026	0.054597	0.063187	0.083046	0.027134	-0.05608	-0.07743	0.068755	0.032269	0.004975	0.106432	0.023049	0.008647	-0.0068	0.057459	0.026131	-0.00312	0.070093
2014-01-31	06018	-0.0310	1 -0.04357	0.028048	-0.03926	-0.01152	-0.1137	-0.08134	-0.05942	0.077678	0.012463	0.19292	-0.00154	-0.06124	0.082811	-0.09048	0.04646	0.044288	-0.06293	-0.06053	-0.04395	-0.0617
2014-02-28	0)20707	-0.0291	6 0.085106	0.025464	0.129597	0.159149	0.081633	-0.05616	0.153909	0.095599	0.028202	0.113841	0.035167	0.059766	0.019699	0.06014	0.067918	0.028478	0.07363	0.03774	0.009372	0.077297
2014-03-31	01623	0.046154	4 -0.03193	-0.07627	0.056331	-0.04183	0.080863	0.063813	-0.01881	0.077101	0.006516	-0.13954	-0.01778	0.042757	0.096212	0.035612	0.01955	0.009163	-0.01369	0.004822	-0.03331	-0.03287
2014-04-30	-00508	0.011905	5 0.005972	-0.09025	-0.02104	-0.06161	0.01995	-0.00925	-0.01272	0.008144	0.009335	0.0399	0.001518	0.006539	0.046648	0.075772	0.00267	0.062179	-0.02888	0.062388	-0.00625	0.023888
2014-05-31	0.0236	-0.02422	2 0.032783	-0.03757	0.038481	0.046199	-0.022	-0.04844	0.020801	0.046556	0.03207	0.051327	0.002707	0.023003	0.010565	0.024002	-0.04745	-0.00855	0.046552	0.017692	0.122737	0.006829
2014-06-30	0)16656	0.10283	7 0.022244	0.102632	0.073147	0.121165	0.0475	0.089077	0.072131	-0.03453	0.03	hic w	ill ha	Ourr	-2147 D	ata Er	ama	ucod	.036831	0.009432	-0.00711	-0.01507
2014-07-31	04048	-0.06045	5 0.029829	0.018298	0.003587	-0.04491	-0.06683	-0.02994	0.025902	-0.0749	-0.	his w	III be	oui i	aw D	aları	anne	useu	0.07241	-0.04764	0.058492	-0.06867
2014-08-31	0)25109	0.039014	4 0.002849	0.017578	0.051832	0.04037	0.066496	0.059724	0.009509	0.0539	0.03		f	or th	e ana	lycic			.017614	0.078492	0.006241	0.087287
2014-09-30	-04866	-0.06588	8 -0.01539	-0.04683	-0.11682	-0.03769	-0.18225	-0.0511	-0.02274	-0.06042	-0.0		ı	OI LII	C alla	19313			0.02245	-0.03639	-0.00116	-0.05157
2014-10-31	0.)25403	-0.00776	6 0.048088	0.32058	-0.0404	0.013441	-0.17889	-0.00284	0.0344	0.222554	-0.00883	0.154022	0.032185	0.056705	0.041448	-0.10083	0.104618	0.11741	0.02753	-0.00833	0.104916	0.038638
2014-11-30	0	-0.0142	0.021106	0.083257	0.085213	0.05077	-0.00357	0.01902	0.068118	0.108961	0.011305	0.018499	0.030763	0.050887	0.031573	-0.14008	0.018186	-0.01354	0.02746	0.022961	0.066034	-0.02282
2014-12-31	0.)22765	-0.0072	0.011458	0.071509	-0.06928	-0.0133	-0.04301	0.042487	0.002783	0.012367	0.018462	-0.05064	0.008527	0.030814	-0.08668	0.012203	0.070053	0.055083	0.006709	0.02208	-0.00977	0.032771
2015-01-31	-(.06579	-0.1125	6 -0.00578	0.359432	0.037221	-0.03535	-0.03745	-0.03166	0.0096	0.13571	-0.19741	-0.00967	-0.02164	-0.00655	-0.00873	-0.08575	-0.01843	0.03442	-0.13274	-0.12748	0.054237	-0.08987
2015-02-28	.09075	0.061375	5 0.058311	0.174913	0.115789	0.127905	0.210117	0.053036	0.072278	-0.06218	0.172192	-0.01566	0.051337	0.011606	-0.05511	0.112461	-0.06338	-0.08327	0.011154	0.132187	0.081115	0.109395
2015-03-31	0.)28269	-0.00925	5 -0.02195	0.177496	-0.0253	-0.06523	-0.13826	-0.00758	-0.0311	0.039749	-0.06594	-0.0392	0.014972	0.008074	-0.12628	-0.09603	-0.00495	-0.0231	-0.04253	-0.00976	0.10617	-0.01129
2015-04-30	-01531	0.031128	8 0.001943	-0.11679	0.00396	0.028672	-0.15672	0.052845	-0.05191	-0.03203	0.129826	-0.02349	-0.03249	-0.02122	0.038541	0.133048	-0.02986	0.011022	-0.00858	0.027377	0.005542	-0.00228
2015-05-31	01301	0.02641	5 0.046963	-0.05536	0.106924	0.039837	0.00885	-0.01092	0.023228	0.009054	0.007538	-0.03185	0.032486	-0.03359	-0.06859	-0.12198	-0.01734	-0.0102	0.029309	0.041215	-0.01522	0.025563
2015-06-30	-0.00032	-0.025	5 0.009877	0.100636	-0.04157	0.024276	0.052632	-0.02262	-0.06766	-0.00325	-0.08113	0.103333	-0.02143	-0.03639	-0.10779	-0.00948	-0.06339	-0.05898	-0.02509	0.054769	-0.05526	0.018973

S&P 500 Monthly Returns From 2013-01-31 to 2017-12-31

Analysis Setup & Process

Investment Universe A collection of investable instruments and their characteristics from which portfolios may be built.

Portfolio Generator A function with the ability to randomly sample an investment universe and produce portfolios.

Portfolio Universe A collection of portfolios and their characteristics on which analysis may be done.

```
class InvestmentUniverse:
   def init (self, universe):
       self.universe = universe
       self.tickers = pd.DataFrame(data=universe.columns,
                                    index=pd.RangeIndex(1, universe.T.count()[0]+1),
                                    columns=['Ticker'])
       self.dates = pd.DataFrame(data=universe.index.values,
                                 index=pd.RangeIndex(1, universe.count()[0]+1),
                                 columns=['Date'])
        self.returns = universe
        self.expected returns = pd.DataFrame(data=self.returns.mean(),
                                            columns=['ExpectedReturn'])
                                                                                     Investment
        self.variances = pd.DataFrame(data=self.returns.var(),
                                                                                   Characteristics
                                      columns=['Variance'])
        self.volatilities = pd.DataFrame(data=self.returns.std(),
                                        columns=['Volatility'])
       self.correl_mtx = self.returns.corr()
       self.covar_mtx = self.returns.cov()
       self.covar mtx diag = pd.DataFrame(data=np.diag(self.returns.var()),
                                          index=self.tickers['Ticker'].values,
                                          columns=self.tickers['Ticker'].values)
       self.covar mtx offdiag = self.covar mtx - self.covar mtx diag
       self.volsumprod mtx = self.volatilities.dot(self.volatilities.T)
   def get ticker count(self):
       return self.tickers.count()[0]
   def get date count(self):
       return self.dates.count()[0]
```

Step1: Investment Universe

For this presentation, **universe** is the S&P 500 Monthly Returns DataFrame.



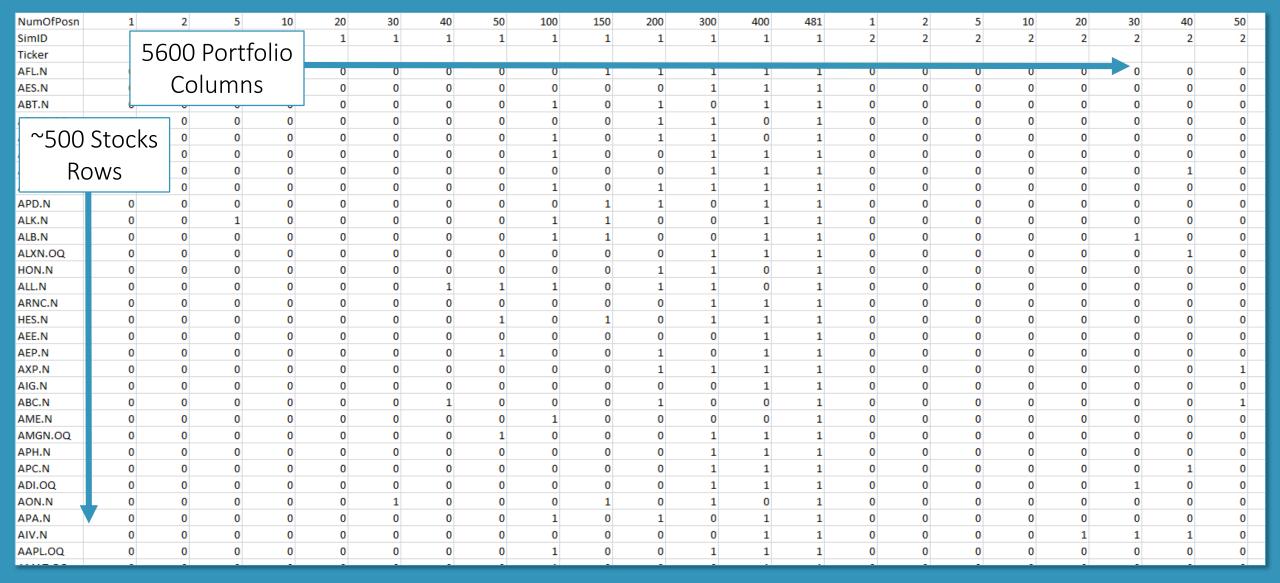
```
def portfolio generator(investment universe,
                        position_list,
                        number of simulations):
    row index = investment universe.tickers.index
    columns = tuple(itertools.product(position list, range(1, number of simulations+1)))
    row index names = ['TickerID']
    columns names = ['NumOfPosn', 'SimID']
    portfolio generation mtx = blank data frame(len(row index),
                                                len(columns),
                                                row index,
                                                                      Random
                                                columns,
                                                                      sampler
                                                row index names,
                                                columns names)
    for j in range(len(position_list)):
        for i in range(1, number of simulations+1, 1):
           pf_sample = list(random.sample(list(row_index), position_list[j]))
           for k in range(len(pf sample)):
                portfolio_generation_mtx[position_list[j],i][pf_sample[k]] = 1
    portfolio generation mtx.index = investment universe.tickers['Ticker']
   return portfolio generation mtx
```

Step2: Portfolio Generator

For this presentation,
position_list is set as
[1,2,5,10,20,30,40,50,100,150,
200,300,400,481] and
number_of_simulations is set
at 400.

Therefore the total number of portfolios generated is 5600.





Portfolio Generation Matrix



```
class PortfolioUniverse:
   def init (self,
                 investment universe,
                 position list,
                 number of simulations):
       self.investment universe = investment_universe
       self.position list = position list
       self.number of simulations = number of simulations
       self.portfolio generation mtx = portfolio generator(self.investment universe,
                                                           self.position list,
                                                           self.number of simulations)
       def get number of different positions(self):
            return len(self.position list)
                                                                                Portfolio
       self.number of different positions = get number of different positions
                                                                                 Weights
       def get number of portfolios(self):
            return self.number of different positions*self.number of simulations
       self.number of portfolios = get number of portfolios(self)
       self.weights = self.portfolio generation mtx/self.portfolio generation mtx.sum()
       def get pf returns(self):
            pf_returns = blank_data_frame(self.investment_universe.get_date_count(),
                                         self.number of portfolios,
                                         self.investment universe.dates['Date'].values,
                                         self.portfolio generation mtx.columns,
                                         ['Date'],
                                         self.portfolio generation mtx.columns.names)
           for j in self.weights.columns.levels[0]:
               for i in self.weights.columns.levels[1]:
                    pf returns[j,i] = self.weights[j,i].dot(self.investment universe.returns.T)
            return pf returns
       self.returns = get pf returns(self)
```

Step 3: Portfolio Universe

Note: Each investment held by a portfolio within the portfolio universe is equally weighted.

This means that their respective weight equals 1/n where n represents the number of investments within the portfolio.



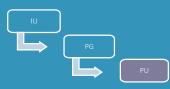
```
def portfolio expected return(pf weight, investment universe):
    return pf weight.dot(investment universe.expected returns)
def portfolio variance(pf weight, investment universe):
    return pf weight.dot(investment universe.covar mtx.dot(pf weight))
def portfolio volatility(pf weight, investment universe):
    return portfolio variance(pf weight, investment universe)**0.5
def portfolio riskadj expected return(pf weight, investment universe):
   return portfolio expected return(pf weight, investment universe)/portfolio volatility(pf weight, investment universe)
def portfolio variance term1(pf weight, investment universe):
    return pf weight.dot(investment universe.covar mtx diag.dot(pf weight))
def portfolio variance term2(pf weight, investment universe):
   return pf weight.dot(investment universe.covar mtx offdiag.dot(pf weight))
def portfolio undiversified variance(pf weight, investment universe):
    return pf weight.dot(investment universe.volsumprod mtx.dot(pf weight))
def portfolio undiversified volatility(pf weight, investment universe):
    return portfolio undiversified variance(pf weight, investment universe)**0.5
```

Portfolio Metrics



Sim	ID NumOfPosn	expected_retu	urns	volatilities	riskadj_expected_returns	variances	variances_term1	variances_term2	undiversified_variances	undiversified_volatilities
	1 1	0.0	1502	0.04583	0.32773	0.00210	0.0021	0.00000	0.00210	0.04 583
	1 2	0.0	1158	0.04916	0.23562	0.002 42	0.0021	0.00031	0.00363	0.06026
	1 5	0.0	1630	0.04228	0,38541	0 00179	0.0010	0.00077	0.00472	0.06871
	1 10	0.0	2124	0.05092	0.	Portfo	olio ¹	0.00145	0.00840	0.09165
	5600 P	ortfolio	152	0.03134	0.	rortic	23	0.00076	0.00409	0.06394
	3000 F) Portfolio		0.02617	0.	Metr	rics 1	0.00057	0.00329	0.05732
	Ro	Rows		0.02769	0.	141001	100	0.00064	0.00434	0.06590
	110	VV 5	350	0.03041	0.44383	0.00092	0.0000	0.00084	0.00421	0.06491
	1 10	0.0	1354	0.02980	0.45429	0.00089	0.0000	0.00084	0.00416	0.06450
	1 15	0.0	1355	0.02989	0.45314	0.00089	0.0000	0.00086	0.00428	0.06546
	1 20	0.0	1328	0.02871	0.46272	0.00082	0.0000	0.00080	0.00397	0.06303
	1 30	0.0	1279	0.02768	0.46221	0.00077	0.0000	0.00075	0.00407	0.06383
	1 40	0.0	1330	0.02882	0.46133	0.00083	0.0000	0.00082	0.00416	0.06451
	1 48	0.0	1351	0.02870	0.47076	0.00082	0.0000	0.00081	0.00415	0.06445
	2	0.0	0178	0.06007	0.02966	0.00361	0.0036	0.00000	0.00361	0.06007
	2	-0.0	0091	0.04623	-0.01961	0.00214	0.0021	-0.00001	0.00422	0.06493
	2	0.0	1952	0.03395	0.57478	0.00115	0.0007	0.00039	0.00373	0.06111
	2 1	0.0	1367	0.03501	0.39043	0.00123	0.0004	0.00073	0.00435	0.06594
	2 2	0.0	1593	0.03170	0.50238	0.00101	0.0002	0.00078	0.00409	0.06398
	2 3	0.0	1397	0.03009	0.46437	0.00091	0.0001	0.00077	0.00381	0.06170
	2 4	0.0	1312	0.03285	0.39932	0.00108	0.0001	0.00093	0.00477	0.06906
	2 5	0.0	1418	0.02733	0.51867	0.00075	0.0001	0.00064	0.00431	0.06566
	2 10	0.0	1285	0.02824	0.45498	0.00080	0.0000	0.00075	0.00430	0.06560
	2 15	0.0	1400	0.02870	0.48789	0.00082	0.0000	0.00079	0.00434	0.06585
	2 20	0.0	1293	0.02852	0.45331	0.00081	0.0000	0.00079	0.00392	0.06260
	2 30	0.0	1373	0.02922	0.46999	0.00085	0.0000	0.00084	0.00421	0.06485
	2 40.	0.0	1345	0.02876	0.46767	0.00083	0.0000	0.00082	0.00412	0.06419
	2 481	0.0	1351	0.02870	0.47076	0.00082	0.0000	0.00081	0.00415	0.06445
	3 1	0.0	1093	0.06113	0.17875	0.00374	0.0037	0.00000	0.00374	0.06113
	3 2	0.0	1724	0.04492	0.38381	0.00202	0.0017	7 0.00025	0.00354	0.05948
	3 5	0.0	1300	0.04105	0.31659	0.00169	0.0008	0.00079	0.00430	0.06561
	2 10	0.0	1252	0.02512	0.30500	0.00122	0.0004	0.00070	0.00420	0.06554

Portfolio Metrics



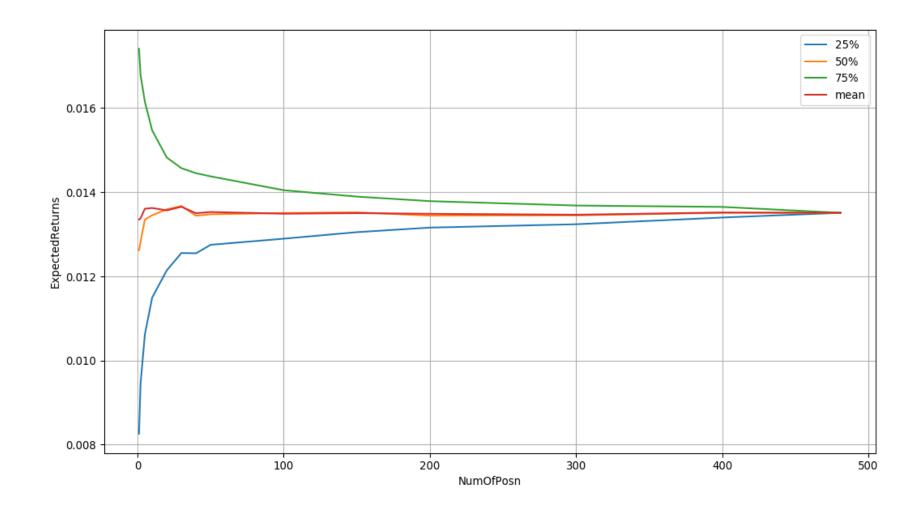
Recap: Portfolio Efficiency & Diversification

How can one use diversification to achieve an efficient portfolio?

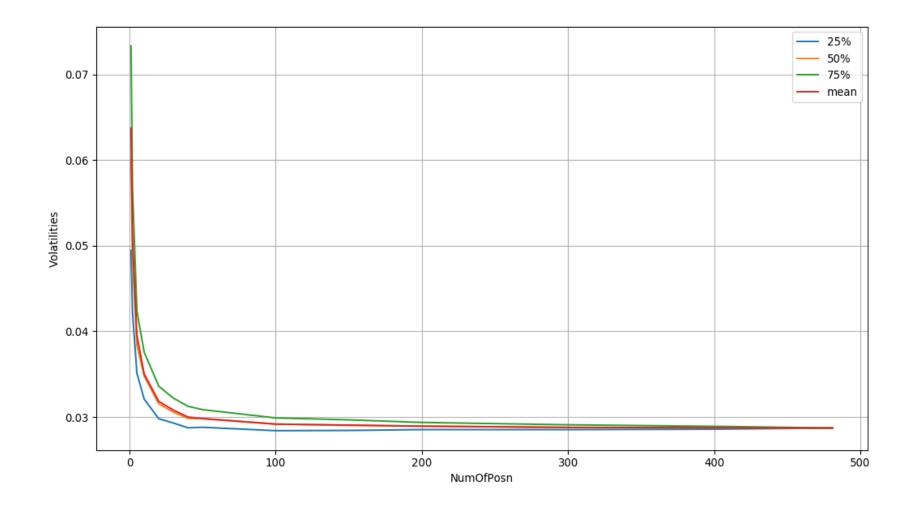
III. Diversification Metrics

Portfolio Efficiency & Diversification

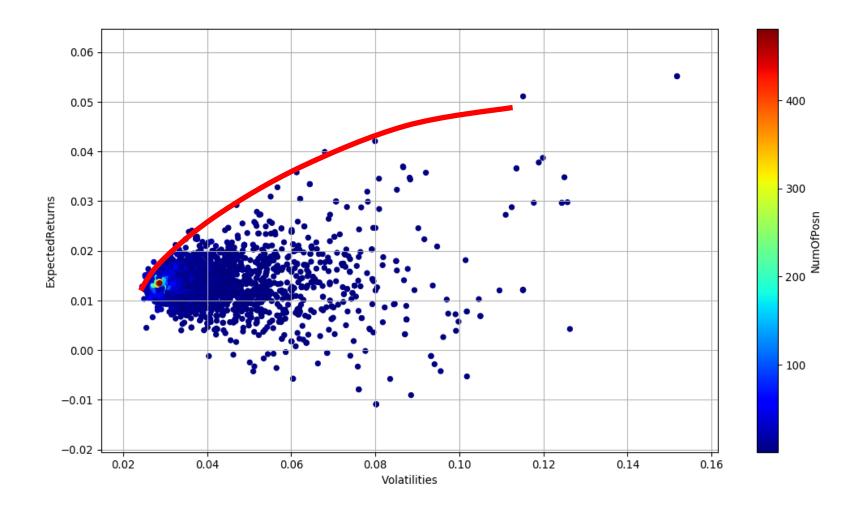
What happens to a portfolio's risk & return profile when you increase its number of investments?



Expected Return vs. Number of Positions in the Portfolio



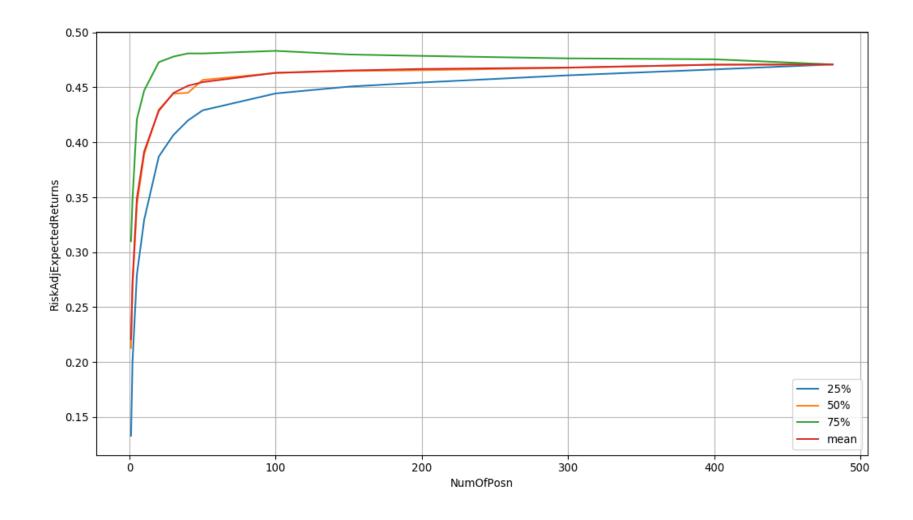
Volatility vs. Number of Positions in the Portfolio



Expected Return vs. Volatility

Portfolio Efficiency & Diversification

What about a portfolio's efficiency as you increase its number of investments?



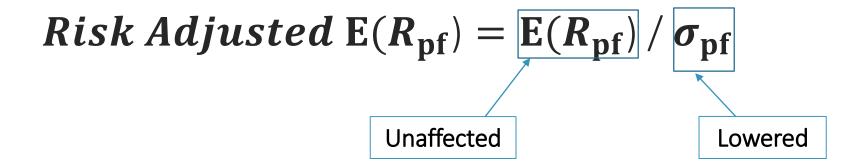
Risk Adjusted Expected Return vs. Number of Positions in the Portfolio

Two Observations:

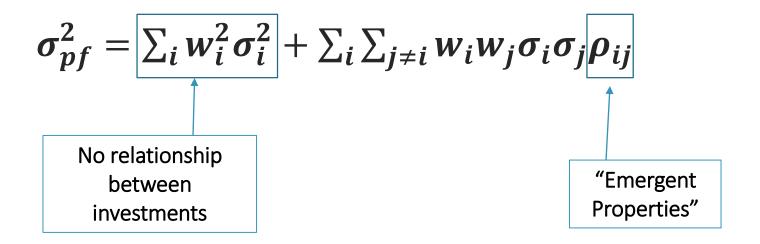
1. As the number of investment $\uparrow \rightarrow$ Portfolio efficiency \uparrow

2. However, it does so at a diminishing marginal rate...

How can diversification be used to target optimal efficiency?



How can diversification be used to target optimal efficiency?



Diversification Metrics

1. Diversification Ratio

2. Average Correlation

3. Diversification Index

$$\sigma_{pf} = \sqrt{\sum_{i} w_{i}^{2} \sigma_{i}^{2} + \sum_{i} \sum_{j \neq i} w_{i} w_{j} \sigma_{i} \sigma_{j} \rho_{ij}}$$
Set equal to 1



$$\sigma_{pf} = \sum_i w_i \sigma_i$$



Undiversified PF Volatility = $\sum_i w_i \sigma_j$

 $PF\ Diversification\ Ratio = [Undiversified\ PF\ Volatility]/[PF\ Volatility]$

def portfolio_diversification_ratio(pf_volatility, pf_undiversified_volatility):
 return pf_undiversified_volatility/pf_volatility



Diversification Ratio $\cong 1$

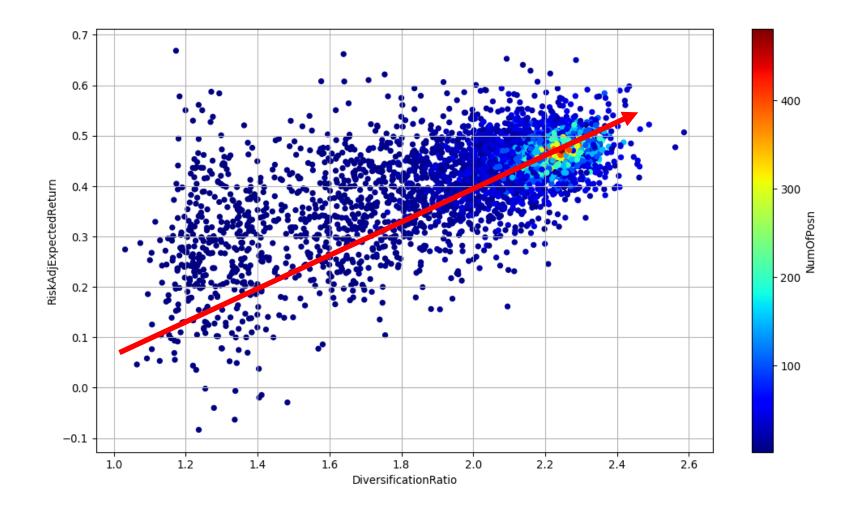
Portfolio has little diversification properties



Diversification Ratio > 1

Portfolio benefits from diversification among its investments





Risk Adjusted Expected Return vs. Diversification Ratio



$$\sigma_{pf} = \sqrt{\sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij}}$$
 Solve for single rho



PF Average Correlation = [PF Variance - PF Variance Term 1]/[Undiversified PF Variance - PF Variance Term 1]

```
def portfolio_avg_correlation(pf_size, pf_variance, pf_variance_term1, pf_undiversified_variance):
    if pf_size == 1:
        portfolio_avg_correlation = 1
    else:
        portfolio_avg_correlation = (pf_variance - pf_variance_term1)/(pf_undiversified_variance - pf_variance_term1)
    return portfolio_avg_correlation
```



 $|Average\ Correlation| \cong 1$

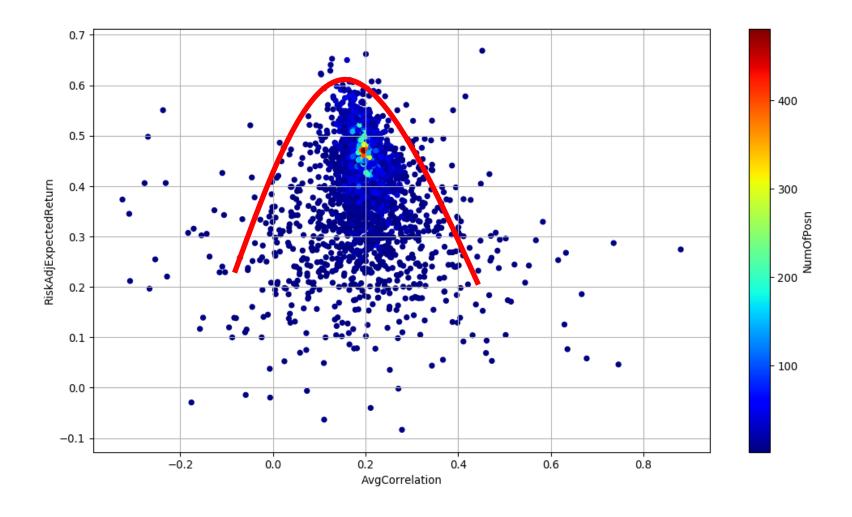
Portfolio has little diversification properties



 $|Average\ Correlation|\cong 0$

Portfolio benefits from diversification among its investments





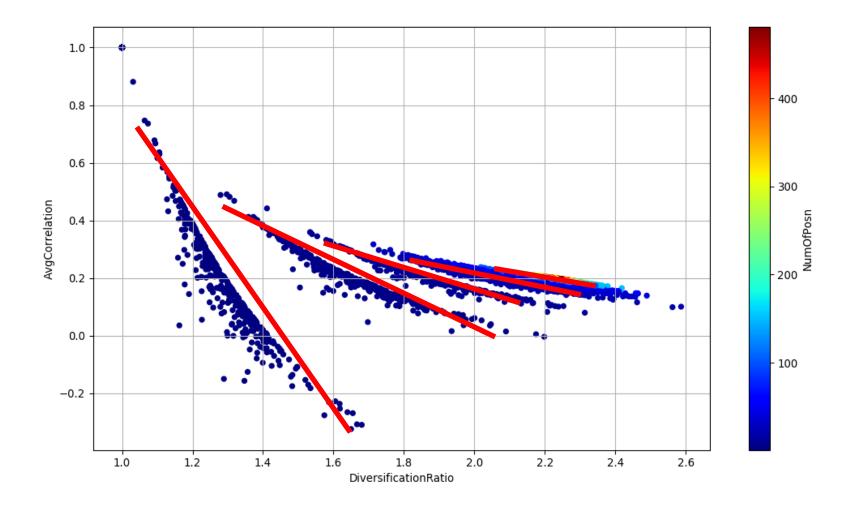
Risk Adjusted Expected Return vs. Average Correlation



Average Correlation vs. Diversification Ratio

Do they tell the same story?





Average Correlation vs. Diversification Ratio



The Volatility of a Portfolio in matrix form:

$$\sigma_{pf} = \sqrt{\text{w'}\Sigma \text{w}}$$

Where:

 σ_{pf}^2 – represents the variance of the portfolio,

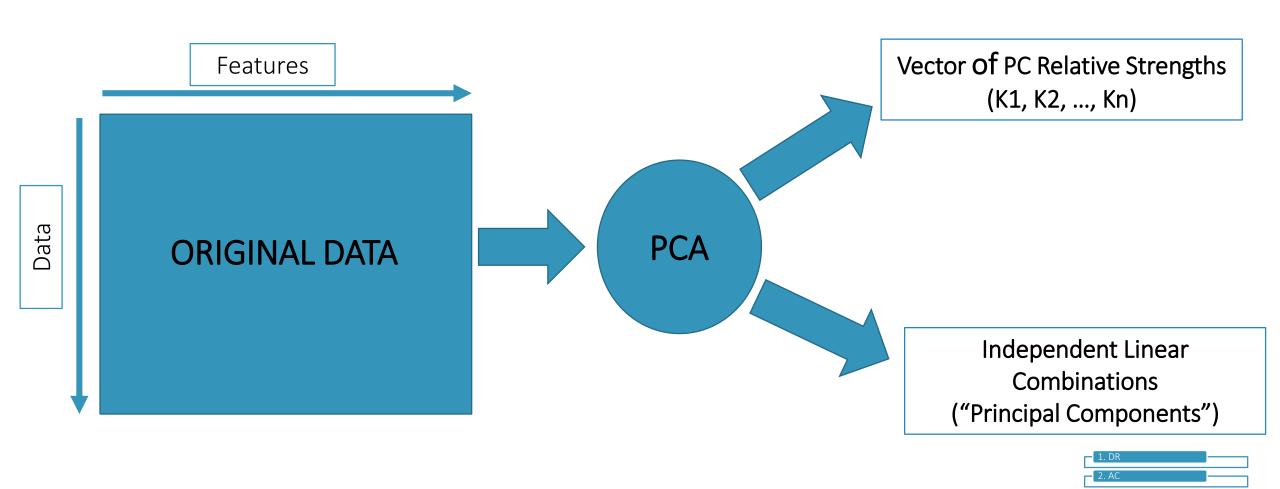
W - represents the portfolio weight vector, and

 Σ – represents the covariance matrix of the portfolio's investments

Decompose into independent factors



Principal Component Analysis Primer



```
def get pf covar mtxs(self):
    pf covar mtks = dict()
    for j in self.weights.columns.levels[0]:
        for i in self.weights.columns.levels[1]:
            pf vector = pd.DataFrame(self.portfolio generation mtx[j,i])
            pf_covar_mtxs[j,i] = pf_vector.dot(pf_vector.T) * self.investment_universe.covar_mtx
    return pf_covar_mtxs
                                                                       SKI earn
self.covar mtxs = get pf covar mtxs(self)
                                                                      PCA object
def portfolio eigenvalue explained variance(pf covar mtx):
    pca = PCA()
    return pca.fit(pf covar mtx).explained variance ratio
def get pf eigenvalue explvars(self):
    pf eigenvalue explvars = pd.DataFrame()
    for j in self.weights.columns.levels[0]:
        for i in self.weights.columns.levels[1]:
            pf_vector = pd.DataFrame(data=portfolio_eigenvalue_explained_variance(self.covar_mtxs[j,i]),
                                    index=pd.RangeIndex(1,len(self.covar mtxs[j,i].index)+1),
                                    columns=pd.MultiIndex.from tuples([(j,i)],names=('NumOfPosn','SimID')))
            pf_eigenvalue_explvars = pd.concat([pf_vector, pf_eigenvalue_explvars], axis=1)
    return pf eigenvalue explvars
```

PCA Explained Variance Ratio



PF Diversification Index =
$$2\sum_{i} i K_{i} - 1$$

Where:

 K_i —represents weighted contribution of each eigenvalue on the system's variance (i.e. PC's relative strength)

```
def portfolio_diversification_index(pf_eigval_explained_var):
    return (2*sum(pf_eigval_explained_var*pf_eigval_explained_var.index))-1
```



PF Diversification Index \cong 1

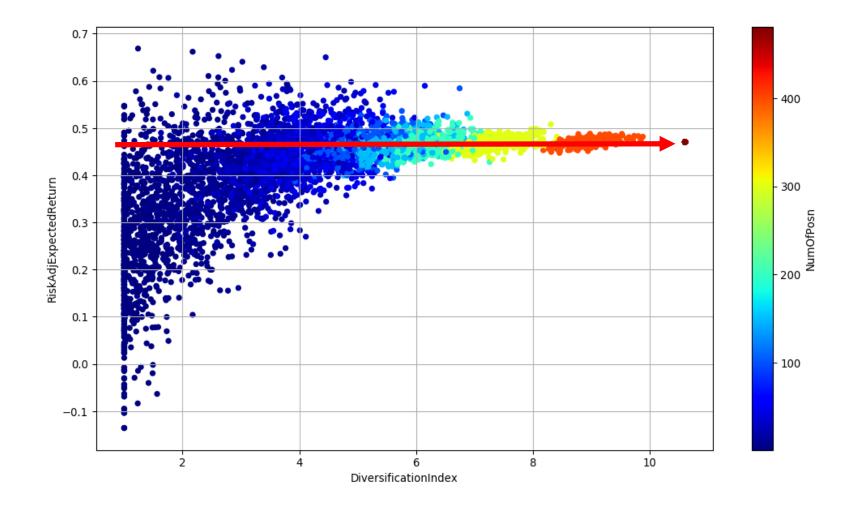
Portfolio has no diversification benefits



PF Diversification Index $\cong N$

Portfolio is ideally diversified





Risk Adjusted Expected Return vs. Diversification Index



Recap: Diversification Metrics

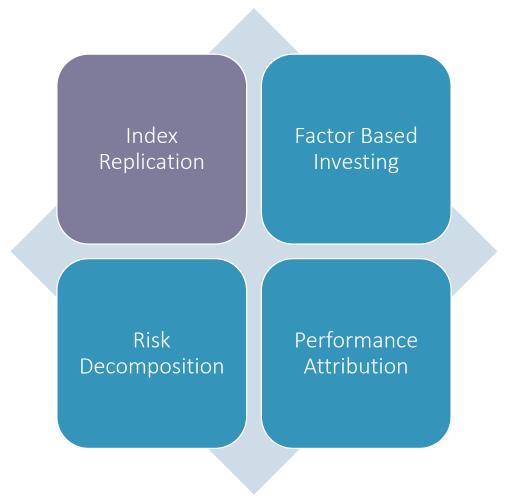
1. Diversification Ratio

2. Average Correlation

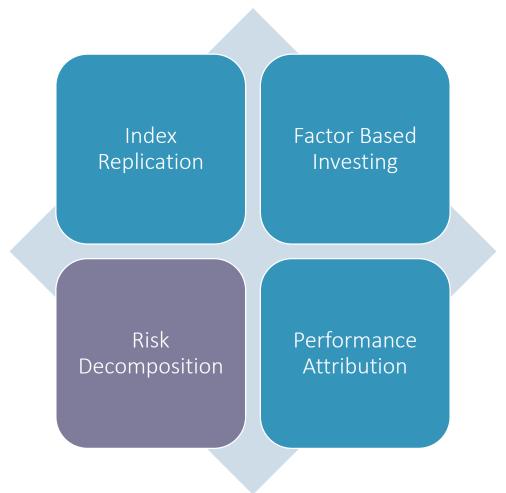
3. Diversification Index

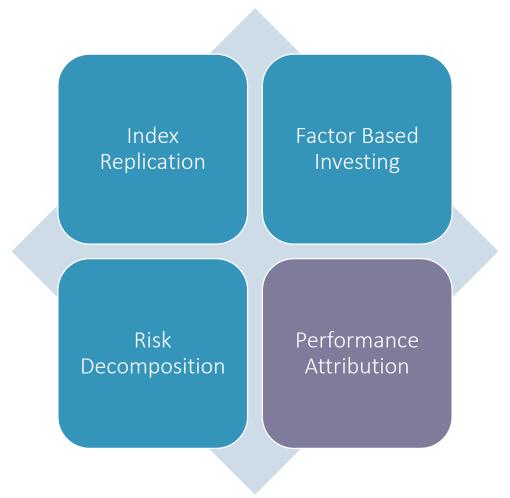
IV. Applications & Resources











Resources

PYTHON LIBRARIES







FINANCIAL LITERATURE



A Portfolio Diversification Index

- Rudin & Morgan
- Journal of Portfolio Management, Winter 2016



Towards Maximum Diversification

- Choueifaty & Coignard
- Journal of Portfolio Management, Fall 2008



Effective Number of Bets

- Attilio Meucci
- 2009a

THANK YOU!

Email: robin.warner@utam.utoronto.ca