Practical Portfolio Optimization

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Based on joint research with

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Goethe University Frankfurt  
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U. Carlos III de Madrid  
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EDHEC Business School

Semi-plenary talk
Fourth International Conference on Continuous Optimization  
Universidade Nova de Lisboa  
Lisbon, July 2013
“The motivation behind my dissertation was to apply mathematics to the stock market” Harry Markowitz

“This is not a dissertation in economics, and we cannot give you a PhD in economics for this” Milton Friedman
Mean-variance efficient frontier

- **Efficient frontier**: Investor concerned only about mean and variance of returns chooses portfolio on *efficient frontier*. 

![Graph showing the efficient frontier with Expected Return on the y-axis and Variance on the x-axis.](attachment:graph.png)
Mean Variance portfolio optimization

\[
\begin{align*}
\min_{\mathbf{w}} & \quad \mathbf{w}^\top \Sigma \mathbf{w} - \mathbf{w}^\top \mathbf{\mu} / \gamma \\
\text{s.t.} & \quad \mathbf{w} \in C
\end{align*}
\]

- \( \mathbf{w} \) portfolio weight vector
- \( \Sigma \) covariance matrix of asset returns
- \( \mathbf{\mu} \) mean asset returns
- \( \gamma \) risk aversion parameter
Implementation: estimation and rebalancing

Portfolio for January 2013

Estimation window

Jan 03

Dec 12

Next month

Time
Portfolio for January 2013

Portfolio for February 2013

Will the portfolios for January 2013 and February 2013 be similar?
Problem: unstable portfolios

- The portfolios for consecutive months usually differ greatly:
  - Unstable portfolios: Extreme weights that fluctuate a lot as we rebalance the portfolio
  - Why?
Problem: unstable portfolios

- The portfolios for consecutive months usually differ greatly:
  - **Unstable portfolios**: Extreme weights that fluctuate a lot as we rebalance the portfolio
  - Why?
  - Estimation error!!!
See also [Chopra and Ziemba, 1993] and [Broadie, 1993].
The 1/N paper
The 1/N paper
DeMiguel, Garlappi, Uppal (RFS, 2009)

**Objective:** Quantify impact of estimation error by comparing mean-variance and equal-weighted portfolio (1/N).

**Why use the 1/N portfolio as a benchmark?**

- **Estimation-error free,**
- **Simple** but not simplistic:
  - Does have **some diversification,** though not “optimally” diversified;
  - With rebalancing $\Rightarrow$ **contrarian**;
  - Without rebalancing $\Rightarrow$ **momentum**.
- **Ancient wisdom**
  - Rabbi Issac bar Aha (Talmud, 4th Century): Equal allocation A third in land, a third in merchandise, a third in cash.
- **Investors use it,** even nowadays.
Thomson Reuters equal weighted commodity index
What we do

- **Empirically:** Compare **fourteen** portfolio rules to $1/N$ across **seven** datasets
  - Sharpe ratio
    \[ SR = \frac{\text{mean}}{\text{std. dev.}} \]

- **Analytically:** Derive **critical estimation window length** for mean-variance strategy to outperform $1/N$.

- **Simulations:** Extend analytical results to models designed to handle estimation error.
What we find

- **Empirically:** None of the fourteen portfolio models consistently dominates $1/N$ across seven separate datasets (SR and turnover).

- **Analytically:** Based on U.S. stock market data, critical estimation window for sample-based mean variance (MV) to outperform $1/N$ is
  - Approximately 3,000 months for 25-asset portfolio
  - Approximately 6,000 months for 50-asset portfolio

- **Simulations:** Even models designed to handle estimation error need unreasonably large estimation windows to outperform $1/N$. 
Portfolios tested

- Bayesian portfolios
Historical return data

Sample mean
Mean prior distribution

Historical return data

Sample mean
Bayes rule

Mean prior distribution

Mean posterior distribution

Historical return data

Sample mean
Portfolios tested

- **Bayesian portfolios**
  - **Diffuse prior** [Barry, 1974], [Klein and Bawa, 1976], [Brown, 1979],
  - **Informative empirical prior** [Jorion, 1986]
  - **Prior belief on asset pricing model** [Pástor, 2000] and [Pástor and Stambaugh, 2000]
Portfolios tested

- Bayesian portfolios

- Portfolios with moment restrictions
  - Minimum-variance portfolio often outperforms mean-variance portfolios; [Jagannathan and Ma, 2003],
  - Value-weighted market portfolio optimal in a CAPM world,
    \[ \Sigma = \nu \mu \mu^\top + \sigma^2 I_N. \]
Portfolios tested

- Bayesian portfolios
- Portfolios with moment restrictions
- Portfolios subject to shortsale constraints
  
  [Jagannathan and Ma, 2003] show they perform well in practice.
Portfolios tested

- Bayesian portfolios
- Portfolios with moment restrictions
- Portfolios subject to shortsale constraints
- Optimal combinations of portfolios
  [Kan and Zhou, 2007]

\[ w_{KZ} = a \cdot w_{\text{mean-variance}} + b \cdot w_{\text{minimum-variance}}, \]

where \( a \) and \( b \) minimize portfolio loss.
**Empirical results: Out-of-sample Sharpe ratios - I**

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<tbody>
<tr>
<td>1/N</td>
<td>0.19</td>
<td>0.14</td>
<td>0.13</td>
<td>0.22</td>
<td>0.16</td>
<td>0.18</td>
</tr>
<tr>
<td>mean var (in sample)</td>
<td>0.38</td>
<td>0.21</td>
<td>0.21</td>
<td>0.29</td>
<td>0.51</td>
<td>0.54</td>
</tr>
</tbody>
</table>

**Classical approach that ignores estimation error**

| mean variance          | 0.08         | -0.04          | -0.07        | 0.22       | -0.07      | 0.00       |

**Bayesian approach to estimation error**

| Bayes Stein            | 0.08         | -0.03          | -0.05        | 0.25       | -0.06      | 0.00       |
| data and model         | 0.14         | -0.05          | 0.10         | 0.02       | 0.07       | 0.24       |

**Moment restrictions**

| minimum variance       | 0.08         | 0.16           | 0.15         | 0.25       | 0.28       | -0.02      |
| market portfolio       | 0.14         | 0.11           | 0.12         | 0.11       | 0.11       | 0.11       |
| missing factor         | 0.19         | 0.13           | 0.12         | 0.06       | 0.15       | 0.15       |
Why does minimum-variance portfolio outperform mean-variance portfolio?

- **In sample**, min-var portfolio has smallest expected return.
Why does minimum-variance portfolio outperform mean-variance portfolio?

- **In sample**, min-var portfolio smallest expected return.

  - Estimation error in mean larger than in variance; [Merton, 1980].
  - Jagannathan and Ma (2003): “estimation error in the sample mean is so large that nothing much is lost in ignoring the mean altogether”.

![Graph showing in-sample and out-of-sample frontiers](image-url)
Mean variance portfolio returns are extreme

![Graph showing portfolio returns over time.]

- **Mean-Variance**
- **Equally Weighted**
## Empirical results: Out-of-sample Sharpe ratios - II

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<td>0.14</td>
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<td>0.54</td>
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### Shortsall constraints

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<th>mean variance</th>
<th>Bayes Stein</th>
<th>minimum variance</th>
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<tr>
<td>mean variance</td>
<td>0.09</td>
<td>0.07</td>
<td>0.08</td>
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<tr>
<td>Bayes Stein</td>
<td>0.11</td>
<td>0.08</td>
<td>0.08</td>
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<tr>
<td>minimum variance</td>
<td>0.08</td>
<td>0.14</td>
<td>0.15</td>
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### Optimal combinations of portfolios

<table>
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<tr>
<th></th>
<th>mean &amp; min-var</th>
<th>1/N &amp; min-var</th>
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<tr>
<td>mean &amp; min-var</td>
<td>0.07</td>
<td>-0.03</td>
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<tr>
<td>1/N &amp; min-var</td>
<td>0.12</td>
<td>0.16</td>
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### 1/N & min-var

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<tr>
<th></th>
<th>0.12</th>
<th>0.16</th>
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</thead>
</table>
Why do shortselling constraints help?

- **Intuitively**, they prevent extreme (large) positive and negative weights in the portfolio.

- **Theoretically**, imposing shortselling constraints is like reducing the covariances assets that we would short; Jagannathan and Ma (2003).

\[ \Sigma = \hat{\Sigma} - \lambda e^T - e\lambda^T \]
### Results: Turnover relative to $1/N$

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<tr>
<td>$1/N$</td>
<td>3.05%</td>
<td>2.16%</td>
<td>2.93%</td>
<td>2.37%</td>
<td>1.62%</td>
<td>1.98%</td>
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#### Mean variance and Bayesian portfolios

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<td>10510</td>
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<td></td>
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<td>2783</td>
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#### Moment restrictions

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<td>minimum variance</td>
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<td>2.47</td>
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<tr>
<td>Bayes Stein</td>
<td>21.65</td>
<td>2.58</td>
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<tr>
<td></td>
<td>7.30</td>
<td>2.27</td>
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<td></td>
<td>1.11</td>
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<td></td>
<td>45.47</td>
<td>3.93</td>
</tr>
<tr>
<td></td>
<td>6.83</td>
<td>1.76</td>
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#### Shortsall constraints

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<th>Bayes Stein</th>
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<td>1.11</td>
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<tr>
<td></td>
<td>3.93</td>
<td>1.76</td>
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</table>
Empirical results: Summary

- **In-sample**, mean-var strategy has highest Sharpe ratio.

- **Out-of-sample**
  - $1/N$ does quite well in terms of Sharpe ratio and turnover.
  - Sample-based mean-var strategy has worst Sharpe ratio.
  - Bayesian policies typically do not out-perform $1/N$.
  - Constrained policies do better than unconstrained, but constraints alone do not help (need extra moment restrictions).

- **Min-var-constrained** does well, but:
  - Sharpe Ratios and CEQ statistically indistinguishable from $1/N$.
  - Better than $1/N$ in only one dataset (20-size/bm portfolios).
  - Turnover is 2-3 times higher than $1/N$. 
When simplicity is a real asset

By Tim Harford

Perhaps the whole ‘don’t put all your eggs in one basket’ school of portfolio allocation is financial wisdom enough

When James Tobin won the Nobel memorial prize in 1981, a journalist asked him to summarise his research in simple language. The great macroeconomist attempted to respond to this challenge, and one wire service dutifully reported that Professor Tobin had won the prize “for his work on the principle of not putting all your eggs in one basket”.

A newspaper cartoon then appeared announcing the award of a Nobel prize for “an apple a day keeps the doctor away”.
Beating 1/N
Beating $1/N$

\[
\begin{align*}
\min_w & \quad w^\top \hat{\Sigma} w - w^\top \hat{\mu} / \gamma \\
\text{s.t.} & \quad w \in C
\end{align*}
\]

**Improve portfolio performance using**

I. better covariance matrix,

II. better mean,

III. better constraints.
I. Better covariance matrix

To estimate covariance matrix better:

1. Use higher-frequency data
   - more accurate estimates of covariance matrix; [Merton, 1980].
I. Better covariance matrix

To estimate covariance matrix better:

1. Use higher-frequency data

2. Use factor models

\[ r = a + B f + \epsilon. \]

- more parsimonious estimates; [Chan et al., 1999].
1. Better covariance matrix

To estimate covariance matrix better:

1. Use higher-frequency data

2. Use factor models

3. Use shrinkage estimators
   - “Honey, I have shrunk the sample covariance matrix”
     [Ledoit and Wolf, 2004b, Ledoit and Wolf, 2004a]

\[
\Sigma_{LW} = \alpha \hat{\Sigma} + (1 - \alpha)I.
\]
Shrinkage estimators

Distribution of deterministic covariance matrix estimator

Bias

Variance $\Sigma$

Variance $\Sigma$

$\Sigma_{LW}$

Distribution of sample covariance matrix estimator

Distribution of shrunk covariance matrix estimator
I. Better covariance matrix

To obtain better estimates of covariance matrix:

1. Use higher-frequency data
2. Use factor models
3. Use shrinkage estimators
4. Use robust optimization
   - [Goldfarb and Iyengar, 2003], [Tütüncü and Koenig, 2003], and others
   \[
   \min_w \max_{\Sigma \in \mathcal{U}} w^T \Sigma w - w^T \hat{\mu} / \gamma \\
   \text{s.t. } w \in \mathcal{C}
   \]
   - Worst-case CVaR
     [Zhu and Fukushima, 2009], [Gotoh et al., 2013].
I. Better covariance matrix

To obtain better estimates of covariance matrix:

1. Use higher-frequency data
2. Use factor models
3. Use shrinkage estimators
4. Use robust optimization
5. Use robust estimation
Portfolio Selection with Robust Estimation

[DeMiguel and Nogales, 2009]

Square function amplifies the impact of outliers
Portfolio Selection with Robust Estimation

- Absolute value function reduces impact of outliers: [Konno and Yamazaki, 1991]
Portfolio Selection with Robust Estimation

M-estimators use smooth error function

Deviation
Portfolio Selection with Robust Estimation

- S-estimators: the impact of outliers is bounded
II. Better mean

To obtain better estimates of mean:

1. Ignore means
II. Better mean

To obtain better estimates of mean:

1. Ignore means

2. Use Bayesian estimates
II. Better mean

To obtain better estimates of mean:

1. Ignore means
2. Use Bayesian estimates
3. Use robust optimization

\[
\min_w \ w^\top \Sigma w - \min_{\mu \in \mathcal{U}} \ w^\top \mu / \gamma \\
\text{s.t. } w \in C
\]
II. Better mean

To obtain better estimates of mean:

1. Ignore means
2. Use Bayesian estimates
3. Use robust optimization
4. Use option-implied information
Improving Portfolio Selection Using Option-Implied Volatility and Skewness

DeMiguel, Plyakha, Uppal, and Vilkov, JFQA

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<tr>
<th>Call Quote</th>
<th>XYZ</th>
<th>Put Quote</th>
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<tbody>
<tr>
<td>* 6.50-7.00</td>
<td>* APR25</td>
<td>* 0.15-0.25</td>
</tr>
<tr>
<td>* 1.55-1.90</td>
<td>* APR30</td>
<td>* 0.15-0.25</td>
</tr>
<tr>
<td>* 0.15-0.25</td>
<td>* APR35</td>
<td>* 3.10-3.50</td>
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<tr>
<td>* 6.50-7.00</td>
<td>* MAY25</td>
<td>* 0.05-0.15</td>
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<tr>
<td>* 4.10-4.50</td>
<td>* MAY27¹⁄₂</td>
<td>* 0.15-0.25</td>
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<tr>
<td>* 1.75-2.00</td>
<td>* MAY30</td>
<td>* 0.20-0.45</td>
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<tr>
<td>* 0.45-0.70</td>
<td>* MAY32¹⁄₂</td>
<td>* 1.15-1.40</td>
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<td>* MAY35</td>
<td>* 3.10-3.50</td>
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<td>* 2.75-3.10</td>
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<td>* 0.90-1.00</td>
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<tr>
<td>* 0.50-0.75</td>
<td>* AUG35</td>
<td>* 3.40-3.80</td>
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- Implied volatilities improve volatility by 10-20%.
- Implied correlations do not improve performance.
- Implied skewness and volatility risk premium proxy mean returns.
  - Improve Sharpe ratio even with moderate transactions costs for weekly and monthly rebalancing.
II. Better mean

To obtain better estimates of mean:

1. Ignore means
2. Use Bayesian estimates
3. Use robust optimization
4. Use option-implied information
5. Use stock return serial dependence
Stock Return Serial Dependence and Out Of Sample Performance, DeMiguel, Nogales, Uppal (2013)

- Stock return serial dependence
  - Contrarian: “buy losers and sell winners”.
  - Momentum: “buy winners and sell losers”.
- Can this be exploited systematically with many assets?
  - Yes, for transaction costs below 10 basis points.

tomorrow
(noun)
The best time to do everything you had planned for today.
II. Better mean

To obtain better estimates of mean:

1. Ignore historical means
2. Use Bayesian estimates
3. Use robust optimization
4. Use option-implied information
5. Use stock return serial dependence
6. Exploit anomalies
Exploit anomalies

- **size**: small firms outperform large firms,

- **momentum**: past winners outperform past losers,

III. Better constraints

To improve performance impose:

1. Shortsage constraints
III. Better constraints

To improve performance impose:

1. **Shortsale constraints**

2. **Parametric portfolios**
   [Brandt et al., 2009] impose constraint

\[
\begin{pmatrix}
w_1 \\ w_2 \\ \vdots \\ w_N \\
\end{pmatrix}
= \begin{pmatrix}
w_{1M} \\ w_{2M} \\ \vdots \\ w_{NM} \\
\end{pmatrix}
+ \begin{pmatrix}
me_1 & btm_1 & mom_1 \\
me_2 & btm_2 & mom_2 \\
\vdots & \vdots & \vdots \\
me_N & btm_N & mom_N \\
\end{pmatrix}
\begin{pmatrix}
\theta_{me} \\ \theta_{btm} \\ \theta_{mom} \\
\end{pmatrix},
\]

me = market equity,
btm = book-to-market ratio,
mom = momentum or average return over past 12 months.
III. Better constraints

To improve performance impose:

1. Shorts ale constraints

2. Parametric portfolios

3. Performance-based regularization
   - Constrain variance of estimators of portfolio mean and CVaR.
III. Better constraints

To improve performance impose:

1. Shortsage constraints
2. Parametric portfolios
3. Performance-based regularization
4. Norm constraints
A Generalized Approach to Portfolio Optimization: Improving Performance by Constraining Portfolio Norms

DGNU (MS, 2009)

\[
\begin{align*}
\min_{w} & \quad w^\top \hat{\Sigma} w \\
\text{s.t.} & \quad w^\top e = 1 \\
& \quad \|w\| \leq \delta
\end{align*}
\]

- Nests \(1/N\), shrinkage covariance matrix of [Ledoit and Wolf, 2004b], and shortsale constraints,
- Diversification: 2-norm,
- Leverage constraint: 1-norm.
Help Wanted
Help wanted

- **Optimization** can make a difference in portfolio selection.

- **Research opportunities**
Help wanted

- **Optimization** can make a difference in portfolio selection.
- **Research opportunities**
  - **Integer variables:**
    - **VaR:**
    - **fixed costs and cardinality constraints:**
      [Roman et al., 2013], “Enhanced indexation based on second-order stochastic dominance”, *Optimization in Finance I, Wed.D.18*. 
Help wanted

- **Optimization** can make a difference in portfolio selection.

- **Research opportunities**
  - Integer variables:
    - VaR:
    - fixed costs and cardinality constraints:
  - Multistage optimization:
    - return predictability,
    - transaction costs,
Help wanted

- **Optimization** can make a difference in portfolio selection.

- **Research opportunities**
  - Integer variables:
    - VaR:
      - fixed costs and cardinality constraints:
  - Multistage optimization:
    - return predictability,
    - transaction costs,
  - Calibration, calibration, calibration:
Same dog, different collar?
Devil Is in One Detail: Calibration

Constraints

Robust optimization

Bayesian portfolios

Shrinkage estimators

Gotoh & Takeda
CMS 2011

Jaganathan
Ma
JoF, 2003
DGNU
MS 2009

Jorion
JFQA 1986

Goldfarb
Iyengar
MOR 2003
Caramanis
Mannor
Xu (2011)

DGNU
MS 2009
Help wanted

- **Optimization** can make a difference in portfolio selection.

- **Research opportunities**
  - Integer variables:
    - value at Risk.
    - fixed costs and cardinality constraints,
  - **Multistage optimization:**
    - return predictability,
    - transaction costs.
  - **Calibration, calibration, calibration:**
    - “Size Matters: Optimal Calibration of Shrinkage Estimators for Portfolio Selection”, [Martin-Utrera, D., Nogales, 2013],
    - choose criterion carefully, get nonparametric.
Help wanted

- **Optimization** can make a difference in portfolio selection.
- **Research opportunities**
  - Integer variables:
    - value at Risk.
    - fixed costs and cardinality constraints,
  - Multistage optimization:
    - return predictability,
    - transaction costs.
  - Calibration, calibration, calibration:
    - “Size Matters: Optimal Calibration of Shrinkage Estimators for Portfolio Selection”, [Martin-Utrera, D., Nogales, 2013],
    - choose criterion carefully, get nonparametric.
  - Statistics/big data/real-time estimation and optimization:
    - high-frequency trading.
High frequency trading

**SPEED TRADING**

HIGH-FREQUENCY TRADING AS SHARE OF ALL STOCK TRADING

<table>
<thead>
<tr>
<th>Region</th>
<th>Percentage</th>
</tr>
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<tbody>
<tr>
<td>US</td>
<td>65%</td>
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<tr>
<td>Europe</td>
<td>45%</td>
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<td>Japan</td>
<td>40%</td>
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<tr>
<td>Australia</td>
<td>30%</td>
</tr>
<tr>
<td>Canada</td>
<td>24%</td>
</tr>
<tr>
<td>Brazil</td>
<td>14%</td>
</tr>
<tr>
<td>Asia without Japan</td>
<td>12%</td>
</tr>
</tbody>
</table>

*Source: NYT*
High frequency trading

The US Flash Crash

Dow Jones Industrial Average

PREVIOUS CLOSE: 10,868.10

CLOSE: 10,520.32 -3.2%

2.46pm 9869.62 -9.2%

On May 6, 2010, Wall Street plunged suddenly and losses gained speed as high speed trading attempted to prevent losses. But almost as quickly the market recovered much of the decline.

SOURCE: NYT
Thank you

Victor DeMiguel
http://www.london.edu/avmiguel/

<table>
<thead>
<tr>
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Portfolio analysis under uncertain means, variances, and covariances.

A mixed integer linear programming formulation of the optimal mean/value-at-risk portfolio problem.

Parametric Portfolio Policies: Exploiting Characteristics in the Cross-Section of Equity Returns.

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