Financial Signal Processing and Systemic Risk Management

Andrew W. Lo, MIT

IEEE SP/SPE Workshop

August 11, 2015

MIT
Laboratory for
Financial Engineering

A Brief History of Investments

January 1926 to December 2013

Asset	Mean	Volatility	Min	Median	Max	CumRet
Large Stocks	10.4	18.8	-29.7	1.3	42.6	$5,922
Small Stocks	12.2	28.8	-36.7	1.5	73.5	$26,044
Long-Term Corp Bonds	5.7	7.8	-20.3	0.4	15.6	$129
Long-Term Govt Bonds	5.5	8.2	-9.5	0.3	15.6	$112
Intermediate-Term Govt Bonds	5.3	4.4	-6.4	0.3	12.0	$93
Treasury Bills	3.5	0.9	-0.1	0.3	1.4	$21

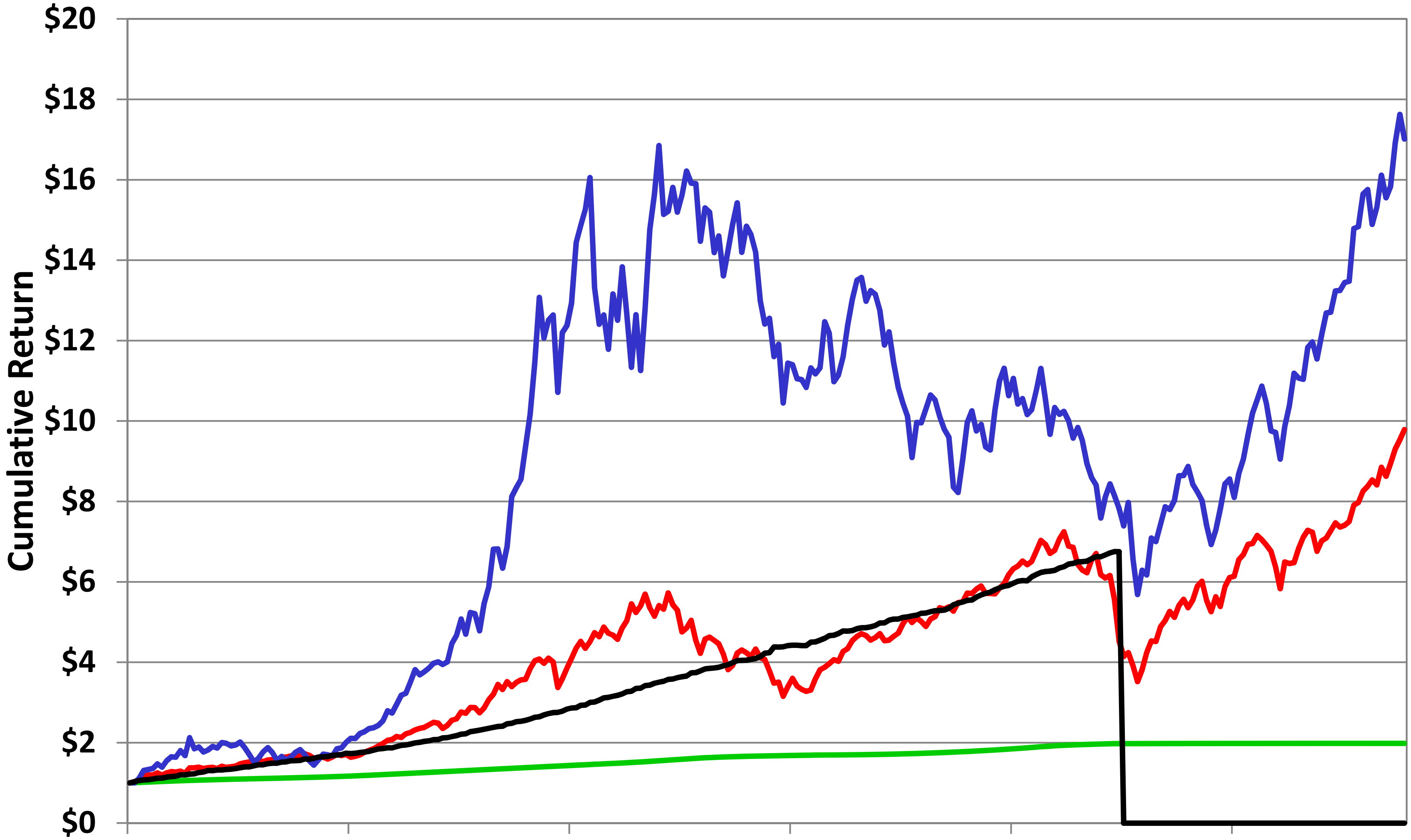
- Investors like return
- Investors dislike risk (volatility); prefer predictability

$$\text{Sharpe Ratio} = \frac{\text{Expected Return} - \text{Riskfree Rate}}{\text{Risk}}$$

What About Perfect Asset Allocation?

$\Rightarrow$ $211,652,388,429

Risk and Reward



The Quant Meltdown of August 2007

Quantitative Equity Funds Hit Hard In August 2007

- Specifically, August 7–9
- Massive reversal on August 10
- Some of the most consistently profitable funds lost too
- Seemed to affect only quants
- No real market news

But Lack of Transparency Is Problematic!

Wall Street Journal **September 7, 2007**

AUGUST AMBUSH

How Market Turmoil Waylaid the 'Quants'

Morgan Stanley Star Is Among Those Battered; No Time for Music Now

By Scott Patterson And Anita Raghavan

Peter Muller, a 43-year-old trader at Morgan Stanley, is used to markets behaving more or less as he expects. But in late July, some unusual patterns perplexed him. Certain investing strategies that historically had posted steady gains started faltering for no evident reason.

Soon, the unusual trading spread from U.S. to Japanese and European

The Quant Meltdown of August 2007

Use Investment Strategy As Research Tool

- Khandani and Lo (2007, 2010) simulate basic mean-reversion strategy of Lehmann (1990) and Lo and MacKinlay (1990)
- Buy previous "losers" and sell previous "winners"
- Bet on mean reversion
- Portfolio weight for stock *i* at date *t*:

$$\omega_{it}(k) = -\frac{1}{N}(R_{it-k} - R_{mt-k}) \quad , \quad R_{mt-k} \equiv \frac{1}{N}\sum_{i=1}^{N} R_{it-k}$$

$$\sum_{i=1}^{N} \omega_{it}(k) = 0 \quad \text{Market Neutral}$$

The Quant Meltdown of August 2007

Use Investment Strategy As Research Tool

Example of Mean-Reversion Strategy, k = 1

Ticker	R_{t-1} (%)	$R_{t-1} - R_{mt-1}$ (%)	I_t ($MM)
C	1.55	1.62	-45.53
IBM	-0.89	-0.82	23.15
INTC	-0.97	-0.90	25.32
MCD	-0.18	-0.11	3.03
MRK	-1.79	-1.73	48.50
MSFT	1.87	1.94	-54.47
Average:	-0.07	Sum:	100.00
		Sum:	-100.00

The Quant Meltdown of August 2007

Use Investment Strategy As Research Tool

$$\text{Profit } \pi_t(k) \;=\; \sum_{i=1}^{n} \omega_{it}(k) R_{it}$$

$$\mathrm{E}[\pi_t(k)] \;=\; \frac{\iota' \boldsymbol{\Gamma}_k \iota}{n^2} - \frac{1}{n}\mathrm{tr}(\boldsymbol{\Gamma}_k) - \frac{1}{n}\sum_{i=1}^{n}(\mu_i - \mu_m)^2$$

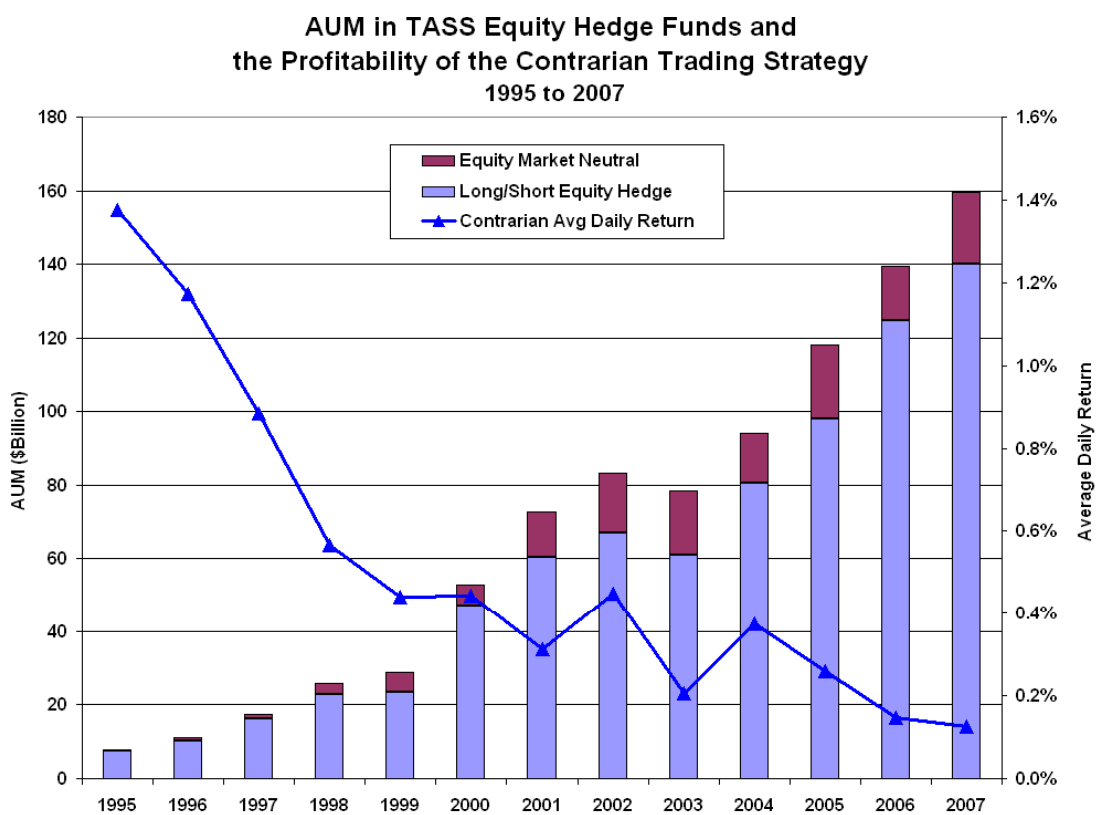
$$\boldsymbol{\Gamma}_k \;\equiv\; \mathrm{E}[(\mathbf{R}_{t-k} - \mu)(\mathbf{R}_t - \mu)']$$

$$\mathrm{E}[\pi_t(k)] \;=\; -\left(\frac{n-1}{n^2}\right)\cdot \mathrm{tr}(\boldsymbol{\Gamma}_k) + \frac{1}{n^2}\left[\iota' \boldsymbol{\Gamma}_k \iota - \mathrm{tr}(\boldsymbol{\Gamma}_k)\right] - \frac{1}{n}\sum_{i=1}^{n}(\mu_i - \mu_m)^2$$

The Quant Meltdown of August 2007

Use Investment Strategy As Research Tool

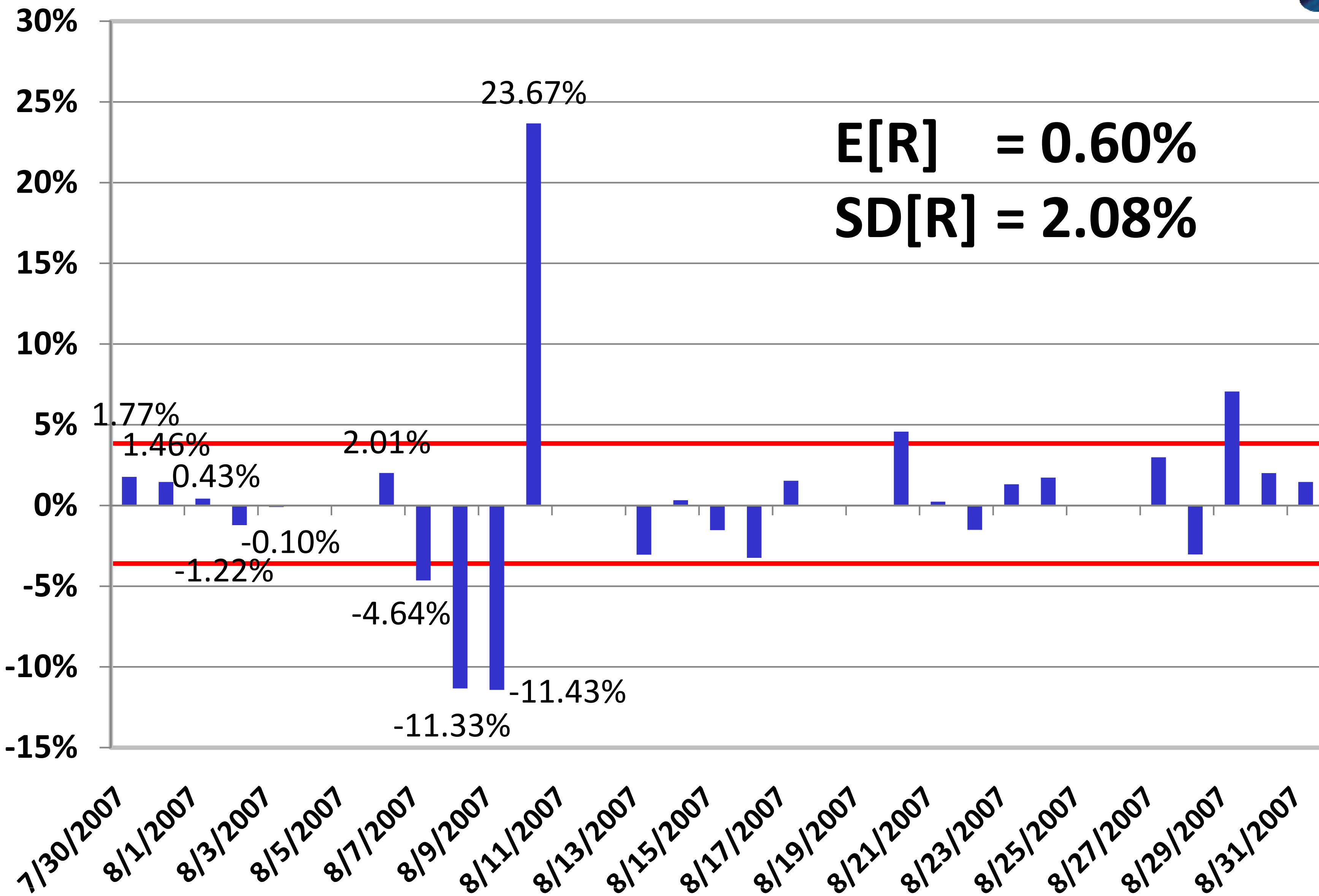
Year	Mean	SD	Sharpe
1995	1.38%	0.40%	53.87
1996	1.17%	0.48%	38.26
1997	0.88%	0.68%	20.46
1998	0.57%	0.84%	10.62
1999	0.44%	1.02%	6.81
2000	0.44%	1.68%	4.17
2001	0.31%	1.43%	3.46
2002	0.45%	0.98%	7.25
2003	0.21%	0.54%	5.96
2004	0.37%	0.53%	11.07
2005	0.26%	0.46%	8.85
2006	0.15%	0.52%	4.47
2007	0.13%	0.72%	2.79



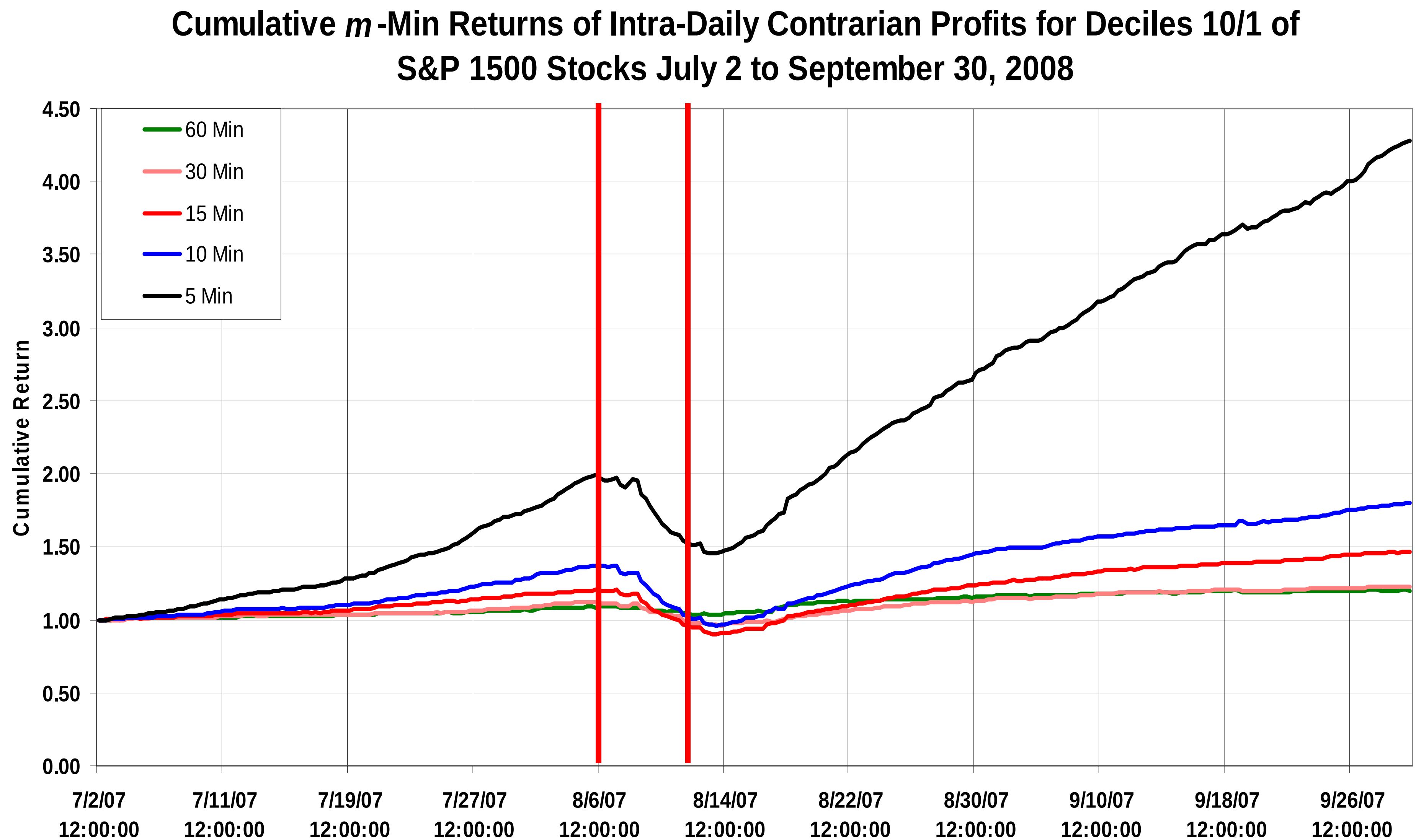
4x: E[R] = 0.60%

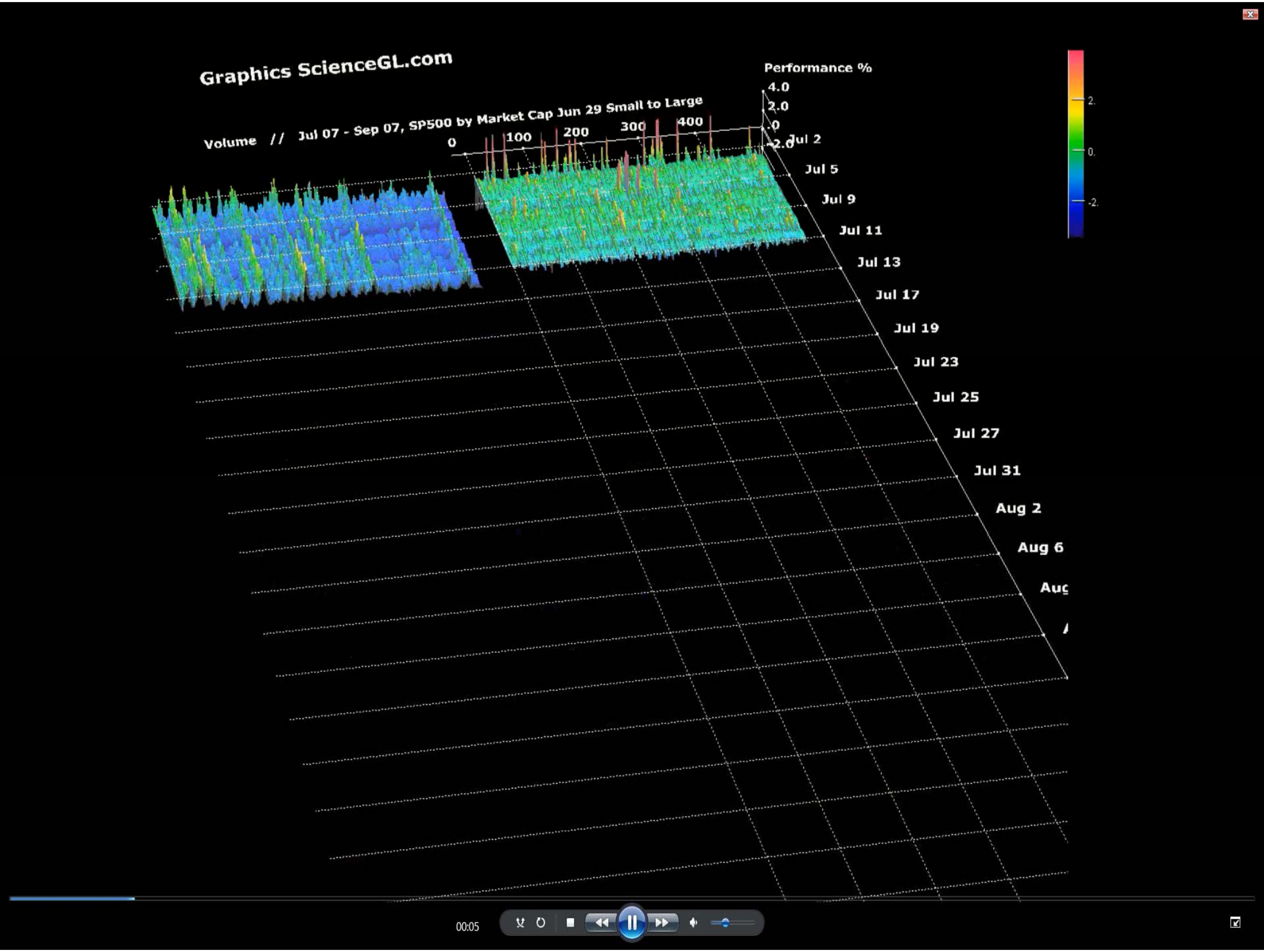
SD[R] = 2.08%

The Quant Meltdown of August 2007



The Quant Meltdown of August 2007





Graphics ScienceGL.com
Volume // Jul 07 - Sep 07, SP500 by Market Cap Jun 29 Small to Large
Performance %
4.0
2.0
0
-2.0
0
100
200
300
400
Jul 2
Jul 5
Jul 9
Jul 11
Jul 13
Jul 17
Jul 19
Jul 23
Jul 25
Jul 27
Jul 31
Aug 2
Aug 6
2.
0.
-2.
00:05

The Unwind Hypothesis

- Losses due to rapid and large unwind of quant fund(s)
- Liquidation was likely forced, given “firesale” prices
- Initial losses caused other funds to cut risk and unwind
- Unwinding caused further losses across broader set of equity funds
- Friday rebound consistent with a liquidity trade, not an information-based trade
- Rebound due to “bargain-hunters”
- Investment horizons differ for different stakeholders

Analyzing Investment Frequency

- Expected returns drive investor behavior

$$R_{pt} = \sum_{i=1}^{n} \omega_{it} R_{it}$$

$$\mathrm{E}[R_{pt}] = \sum_{i=1}^{n} \mathrm{E}[\omega_{it} R_{it}] = \sum_{i=1}^{n} \omega_{it} \mathrm{E}[R_{it}]$$

- But portfolio weights may not be deterministic

$$\omega_{it} = \omega_{it}(\mathbf{X}_{t-1};\theta)$$

$$\mathrm{E}[R_{pt}] = \sum_{i=1}^{n} \mathrm{E}[\omega_{it}(\mathbf{X}_{t-1};\theta) R_{it}] \neq \sum_{i=1}^{n} \omega_{it}(\mathbf{X}_{t-1}) \mathrm{E}[R_{it}]$$

Analyzing Investment Frequency

- Expected return decomposition (Lo, 2008):

$$
\begin{aligned}
\mathrm{E}[R_{pt}] &= \sum_{i=1}^{n} \mathrm{E}[\omega_{it}(\mathbf{X}_{t-1};\theta)R_{it}] = \sum_{i=1}^{n}\Big(\mathrm{Cov}[\omega_{it}, R_{it}] + \mathrm{E}[\omega_{it}]\mathrm{E}[R_{it}]\Big) \\
&= \underbrace{\sum_{i=1}^{n} \mathrm{Cov}[\omega_{it}, R_{it}]}_{\text{Active Component}} + \underbrace{\sum_{i=1}^{n} \mathrm{E}[\omega_{it}]\mathrm{E}[R_{it}]}_{\text{Passive Component}}
\end{aligned}
$$

- Covariances vary across investors

Analyzing Investment Frequency

- Use frequency representation (Chaudhuri and Lo, 2015):

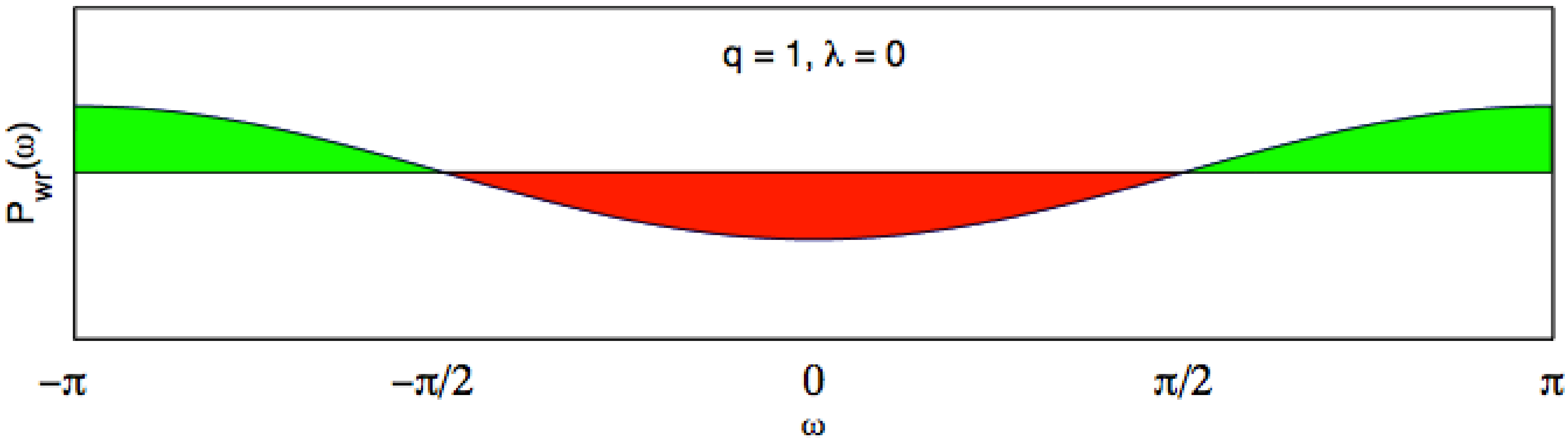
$$\mathrm{E}[R_{pt}] = \int_{-\pi}^{\pi} \sum_{i=1}^{n} P_{\omega_i,R_i}(\nu)\, d\nu$$

$$P_{\omega_i,R_i}(\nu) \equiv \sum_{k=-\infty}^{\infty} \mathrm{Cov}[\omega_{it+k}, R_{it}]e^{-j\nu k} + 2\pi\mathrm{E}[\omega_{it}]\mathrm{E}[R_{it}]\delta(\nu)$$

- Cross power density spectrum
- Decomposes expected return and investment behavior into distinct frequencies

Analyzing Investment Frequency

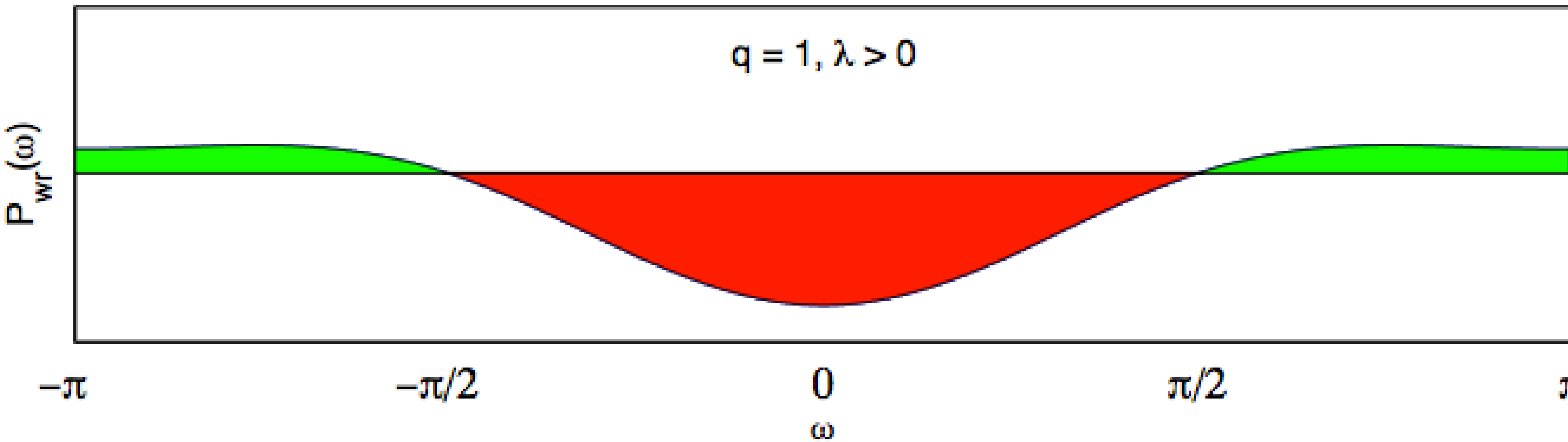
- Mean-reversion strategy with white noise:



- In phase at high frequencies
- Out of phase at low frequencies

Analyzing Investment Frequency

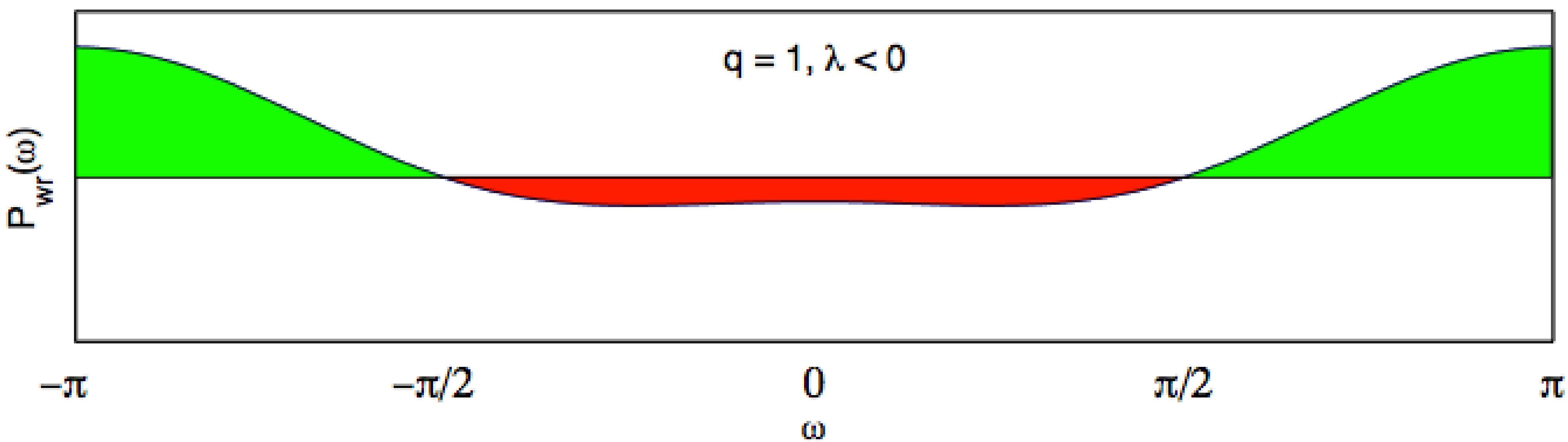
- Mean-reversion strategy with momentum:



- More power at low frequencies (out of phase)

Analyzing Investment Frequency

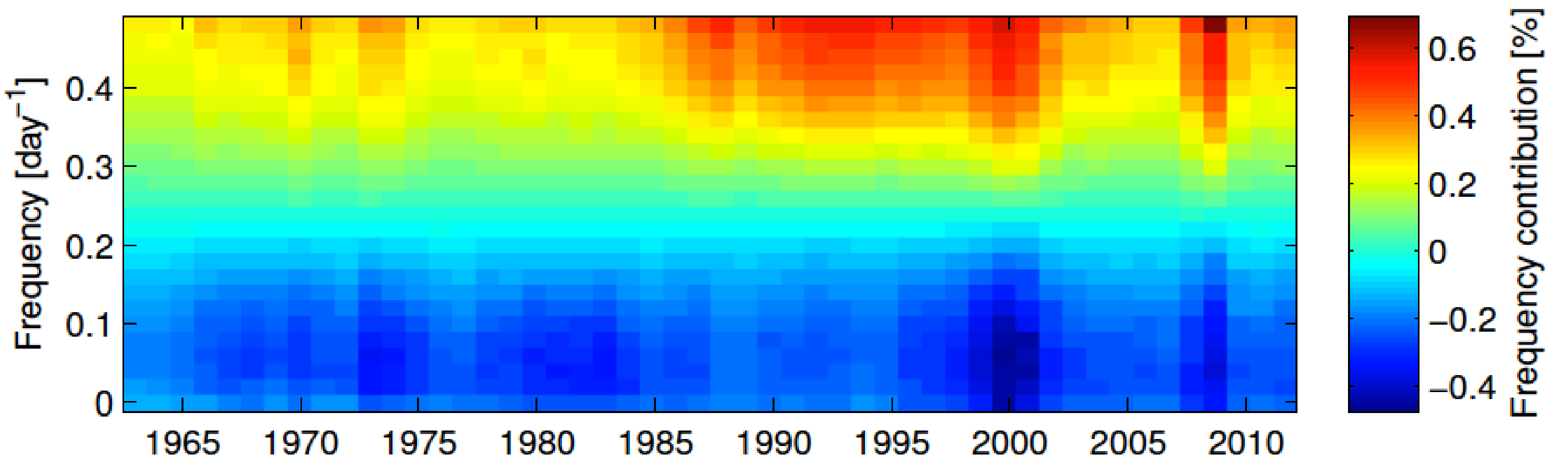
- Mean-reversion strategy with mean reversion:

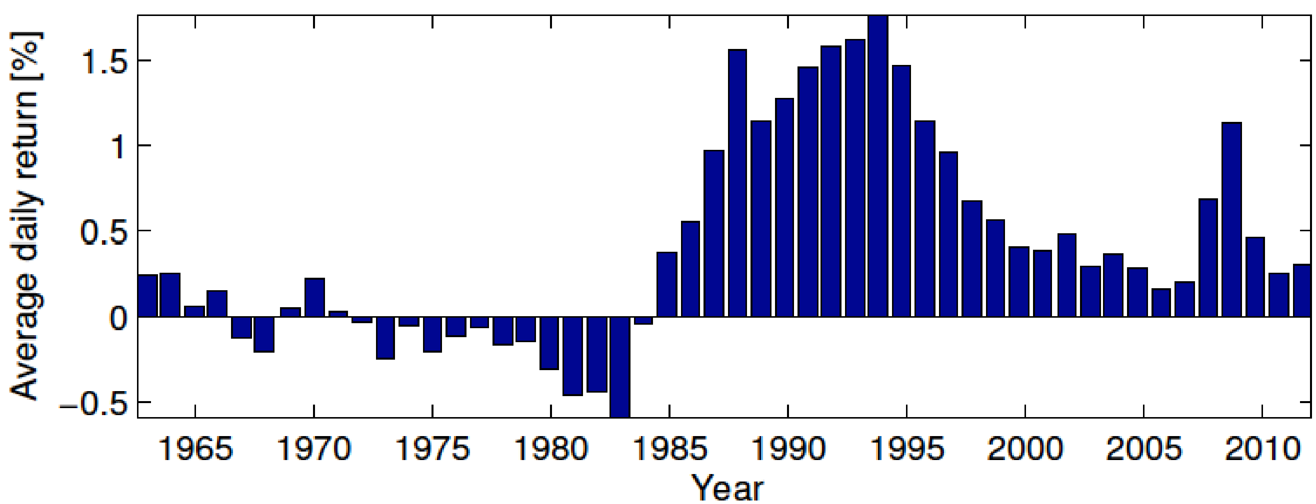


- More power at high frequencies (in phase)

Analyzing Investment Frequency

- Empirical analysis of historical data





Analyzing Investment Frequency

Opens a Large Field of Potential Applications

- Identify key frequencies for each investor type
- Construct frequency-optimized portfolios
- Coupled oscillators
- Are there “resonant frequencies” for the financial system?

Privacy vs. Transparency

Predicting Social Security numbers from public data

Alessandro Acquisti[1] and Ralph Gross

Carnegie Mellon University, Pittsburgh, PA 15213

PNAS 106 (July 2009)

Communicated by Stephen E. Fienberg, Carnegie Mellon University, Pittsburgh, PA, May 5, 2009 (received for review January 18, 2009)

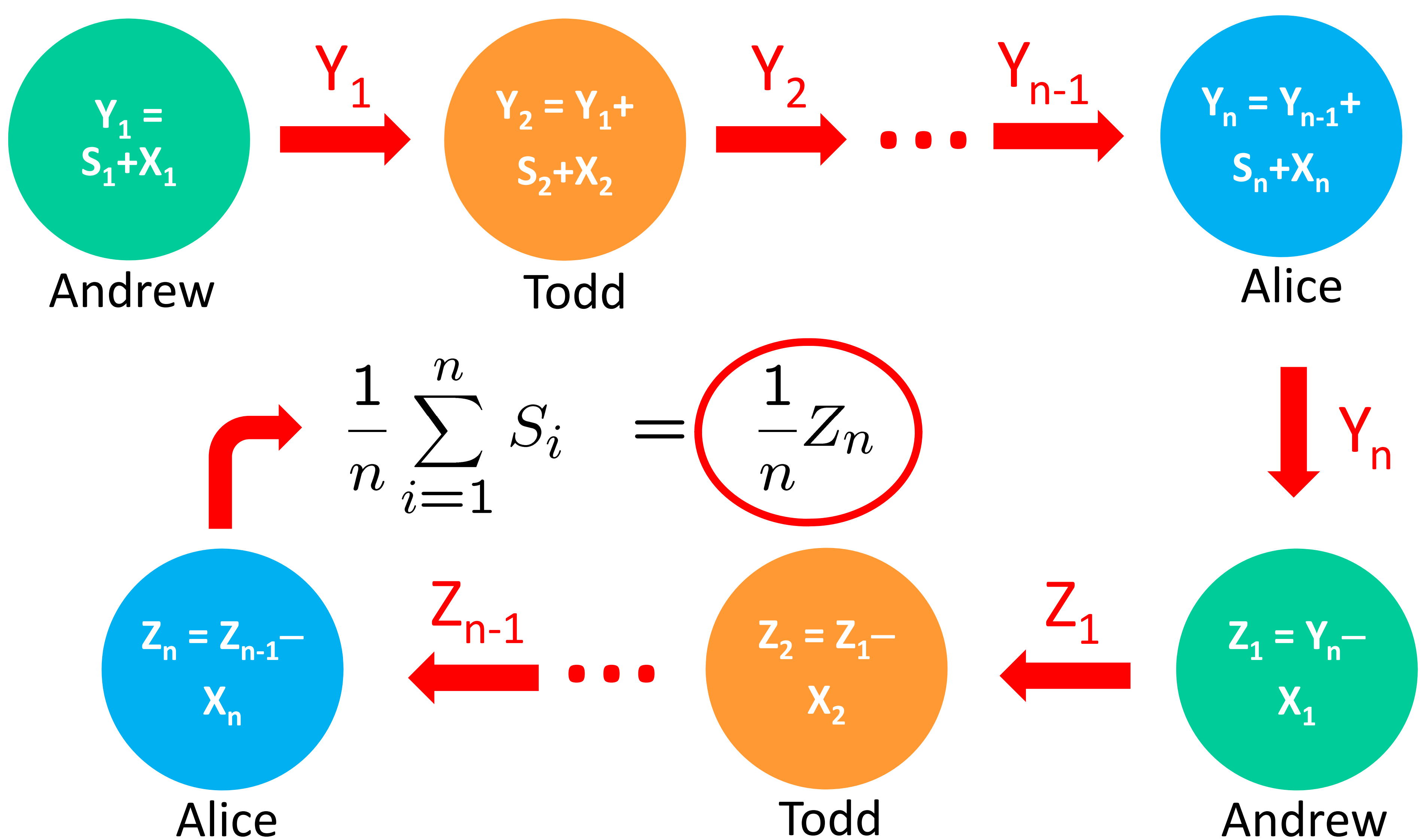
Information about an individual's place and date of birth can be exploited to predict his or her Social Security number (SSN). Using only publicly available information, we observed a correlation between individuals' SSNs and their birth data and found that for younger cohorts the correlation allows statistical inference of private SSNs. The inferences are made possible by the public availability of the Social Security Administration's Death Master File and the widespread accessibility of personal information from multiple sources, such as data brokers or profiles on social networking sites. Our results highlight the unexpected privacy consequences of the complex interactions among multiple data sources in modern information economies and quantify privacy risks associated with information revelation in public forums.

identity theft | online social networks | privacy | statistical reidentification

number (SN). The SSA openly provides information about the process through which ANs, GNs, and SNs are issued (1). ANs are currently assigned based on the zipcode of the mailing address provided in the SSN application form [RM00201.030] (1). Low-population states and certain U.S. possessions are allocated 1 AN each, whereas other states are allocated sets of ANs (for instance, an individual applying from a zipcode within New York state may be assigned any of 85 possible first 3 SSN digits). Within each SSA area, GNs are assigned in a precise but nonconsecutive order between 01 and 99 [RM00201.030] (1). Both the sets of ANs assigned to different states and the sequence of GNs are publicly available (see www.socialsecurity.gov/employer/stateweb.htm and www.ssa.gov/history/ssn/geocard.html). Finally, within each GN, SNs are assigned "consecutively from 0001 through 9999" (13) (see also [RM00201.030], ref. 1.)

Is There A Compromise Between Data Privacy and Transparency?

Secure Multi-Party Computation



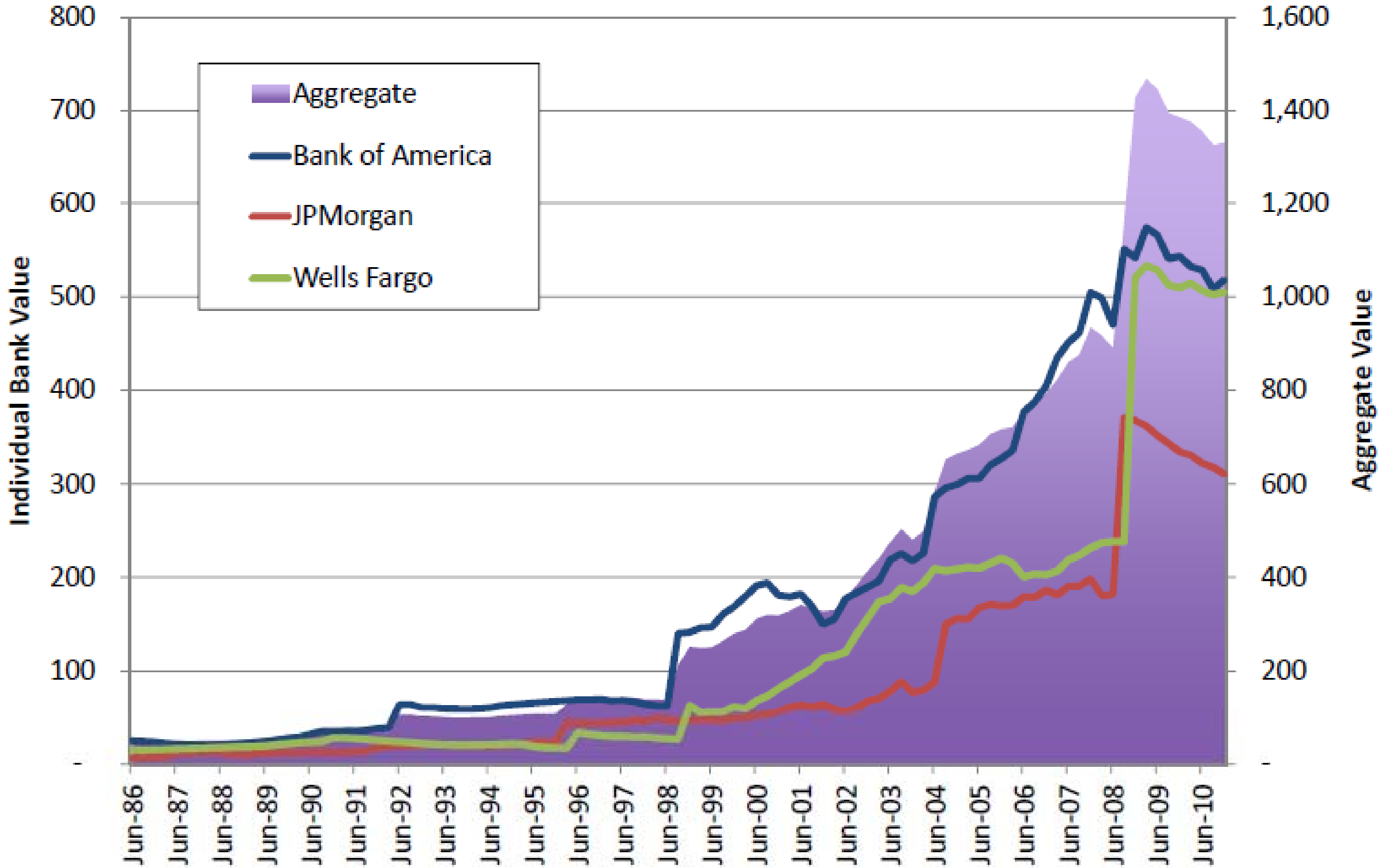
Privacy and Transparency

Transparency and Privacy Can <u>Both</u> Be Achieved

- Abbe, Khandani, and Lo (2012, 2015)
- Individual data is kept private, e.g., RSA
- Encryption algorithms are "collusion-robust"
- Aggregate risk statistics can be computed using encrypted data
  - Means, variances, correlations, percentiles, Herfindahl indexes, VaR, CoVaR, MES, etc.
- Privacy is preserved, no need for raw data!

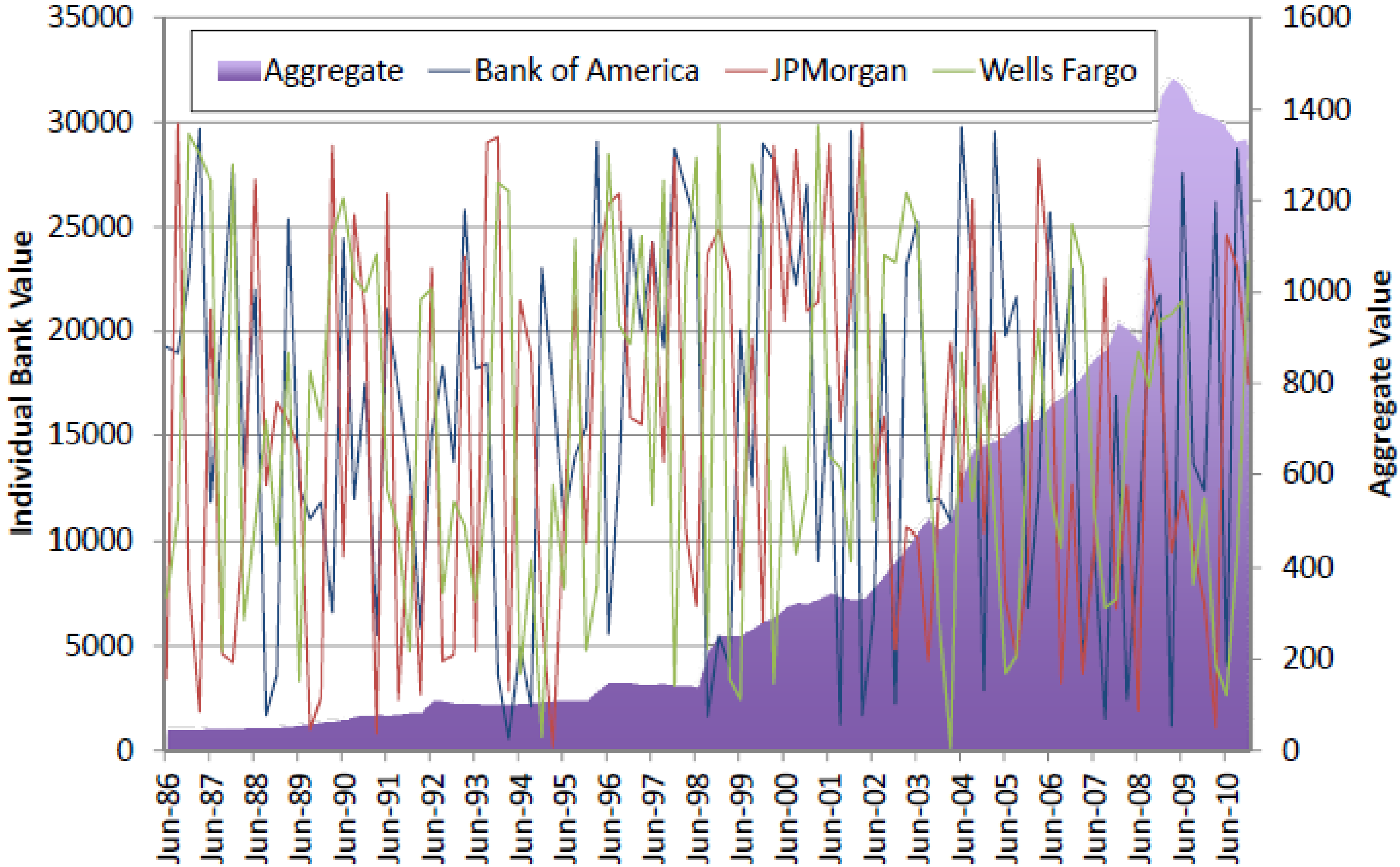
Privacy and Transparency

Real Estate Loans Outstanding



Privacy and Transparency

Real Estate Loans Outstanding



Privacy and Transparency

OFFICE OF
FINANCIAL RESEARCH
U.S. DEPARTMENT OF THE TREASURY

Office of Financial Research
Working Paper #0011
September 4, 2013

Cryptography and the Economics of Supervisory Information: Balancing Transparency and Confidentiality

Mark Flood,[1] Jonathan Katz,[2] Stephen Ong,[3] and Adam Smith[4]

[1] Office of Financial Research, mark.flood@treasury.gov
[2] University of Maryland, jkatz@cs.umd.edu
[3] Federal Reserve Bank of Cleveland, stephen.j.ong@clev.frb.org
[4] Pennsylvania State University and Office of Financial Research, asmith@cse.psu.edu

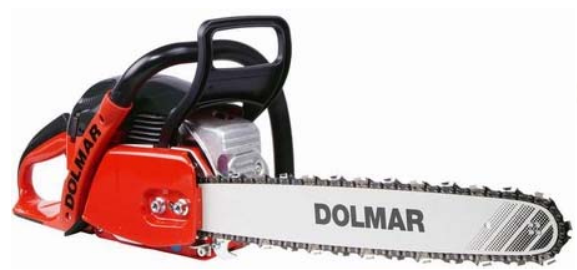
The Office of Financial Research (OFR) Working Paper Series allows staff and their co-authors to disseminate preliminary research findings in a format intended to generate discussion and critical comments. Papers in the OFR Working Paper Series are works in progress and subject to revision.

Views and opinions expressed are those of the authors and do not necessarily represent official OFR or Treasury positions or policy. Comments are welcome as are suggestions for improvements, and should be directed to the authors. OFR Working Papers may be quoted without additional permission.

www.treasury.gov/ofr

Conclusion

- Technology has transformed everything!
- Financial markets are vastly better off
- But new challenges have emerged
- We can do better
- We have to do better



- Regulation has to account for technology and how it interacts with human behavior
- Signal processing can play a critical role in measuring and managing systemic risk

Thank You!