Statistical Arbitrage, Enhanced Indexing and 130/30

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Summary

-- Overview of Statistical Arbitrage as an investment strategy

-- Using ETFs as relative-value indicators

-- Mean-reversion & the Ornstein-Uhlenbeck process

-- Examples of trades

-- Portfolio construction: the PLATA fund

-- Synthetic 130/30 funds constructed from PLATA and Indices

-- Comparison of PLATA+SP with 130/30 Mutual Funds and a 130/30 ETF

-- Conclusions

Statistical Arbitrage

Trading strategy consisting of investing in long-short stocks (or another asset class) with a mean-reversion theme

-- Pairs trading: practiced since the 1990s, invented by Morgan Stanley's prop team

-- ``Factor neutral'' trading: generalizes pairs trading

-- ETF relative-value trading: the subject of this presentation

Idea: measure statistically a time-series of spread between two or more correlated stocks or indices and invest in overbought/undersold spreads.

Trading Universe:
Stocks of more than 1BB cap

Sector	ETF	Num of Stocks	Market Cap		unit: 1M/usd
			Average	Max	Min
Internet	HHH	22	10,350	104,500	1,047
Real Estate	IYR	87	4,789	47,030	1,059
Transportation	IYT	46	4,575	49,910	1,089
Oil Exploration	OIH	42	7,059	71,660	1,010
Regional Banks	RKH	69	23,080	271,500	1,037
Retail	RTH	60	13,290	198,200	1,022
Semiconductors	SMH	55	7,303	117,300	1,033
Utilities	UTH	75	7,320	41,890	1,049
Energy	XLE	75	17,800	432,200	1,035
Financial	XLF	210	9,960	187,600	1,000
Industrial	XLI	141	10,770	391,400	1,034
Technology	XLK	158	12,750	293,500	1,008
Consumer Staples	XLP	61	17,730	204,500	1,016
Healthcare	XLV	109	14,390	192,500	1,025
Consumer discretionary	XLY	207	8,204	104,500	1,007
Total		**1417**	**11,291**	**432,200**	**1,000**

January, 2007

Using ETFs as relative value indicators: e.g. EBAY versus QQQQ

Idea: rather than considering all stock pairs, which requires handling two specific risks per trade and a huge number of pairs, consider a stock and the sector ETF corresponding to its industry

Pro: the relative analysis of a stock compared to its peers is done comparing with an index. We deal with one stock-specific risk at a time, not 2.

Pro: the complexity of the signal generation is significantly reduced and the origin of excess returns is simple to explain

Con: some large cap stocks track too closely the industry, so no signals are available. Equivalently, the strategy can be viewed as somewhat biased to small caps

Con: Some stocks do not fit well the ETF identikit. We leave those to fundamental analysts.

Modeling the Evolution of Stock Residuals

$$\frac{dS_i(t)}{S_i(t)} = \beta_i \frac{dI(t)}{I(t)} + \varepsilon_i(t)$$

Stock returns a sum of a multiple of an ETF return and a residual process

$$\varepsilon_i(t) = \alpha_i dt + dX_i(t)$$

Residual= drift component (expected excess return above mkt.) + increment of a <u>stationary process</u>

$$dX_i(t) = \kappa_i(m_i - X_i(t))dt + \sigma_i dW_i(t)$$

Ornstein-Ulembeck AR-1 process

Statistical Estimation Window=3 months (~ 60 business days) to include at least one earnings announcement

Statistics on the Estimated OU Parameters

ETF	Abs(Alpha)	Beta	Kappa	Reversion days	EquiVol	Abs(m)
HHH	0.20%	0.69	38	7	4%	3.3%
IYR	0.11%	0.90	39	6	2%	1.8%
IYT	0.18%	0.97	41	6	4%	3.0%
RKH	0.10%	0.98	39	6	2%	1.7%
RTH	0.17%	1.02	39	6	3%	2.7%
SMH	0.19%	1.01	40	6	4%	3.2%
UTH	0.09%	0.81	42	6	2%	1.4%
XLF	0.11%	0.83	42	6	2%	1.8%
XLI	0.15%	1.15	42	6	3%	2.4%
XLK	0.17%	1.03	42	6	3%	2.7%
XLP	0.12%	1.01	42	6	2%	2.0%
XLV	0.14%	1.05	38	7	3%	2.5%
XLY	0.16%	1.03	39	6	3%	2.5%
Total	0.15%	0.96	40	6	3%	2.4%

Average over 2006-2007

Trading Signals

We introduce an **s-score** for each stock:

$$s_i(t) = \frac{X_i(t) - m_i}{\sigma_{eq,i}}$$

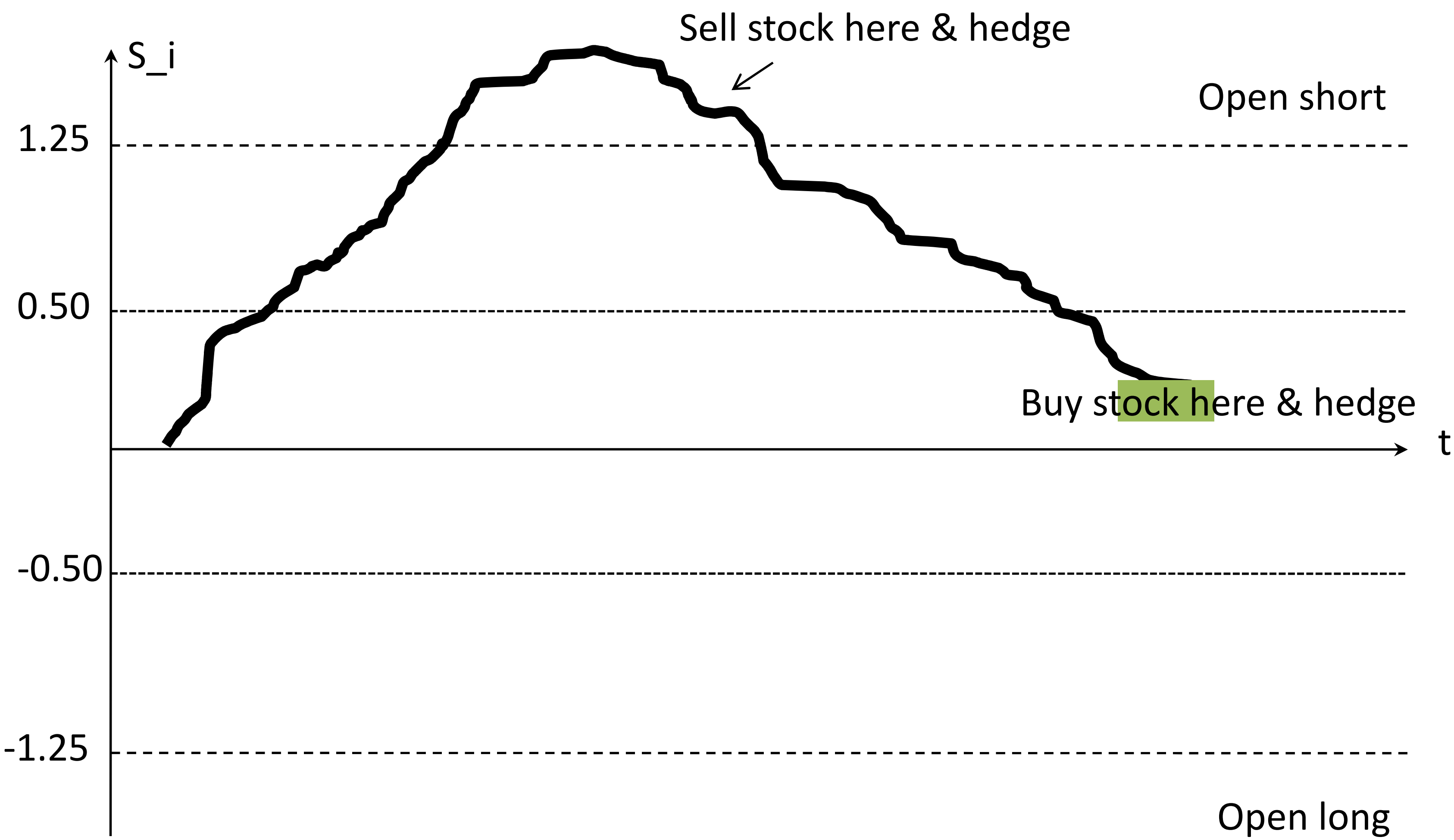
Open long position if $s_i < -1.25$

Open short position if $s_i > +1.25$

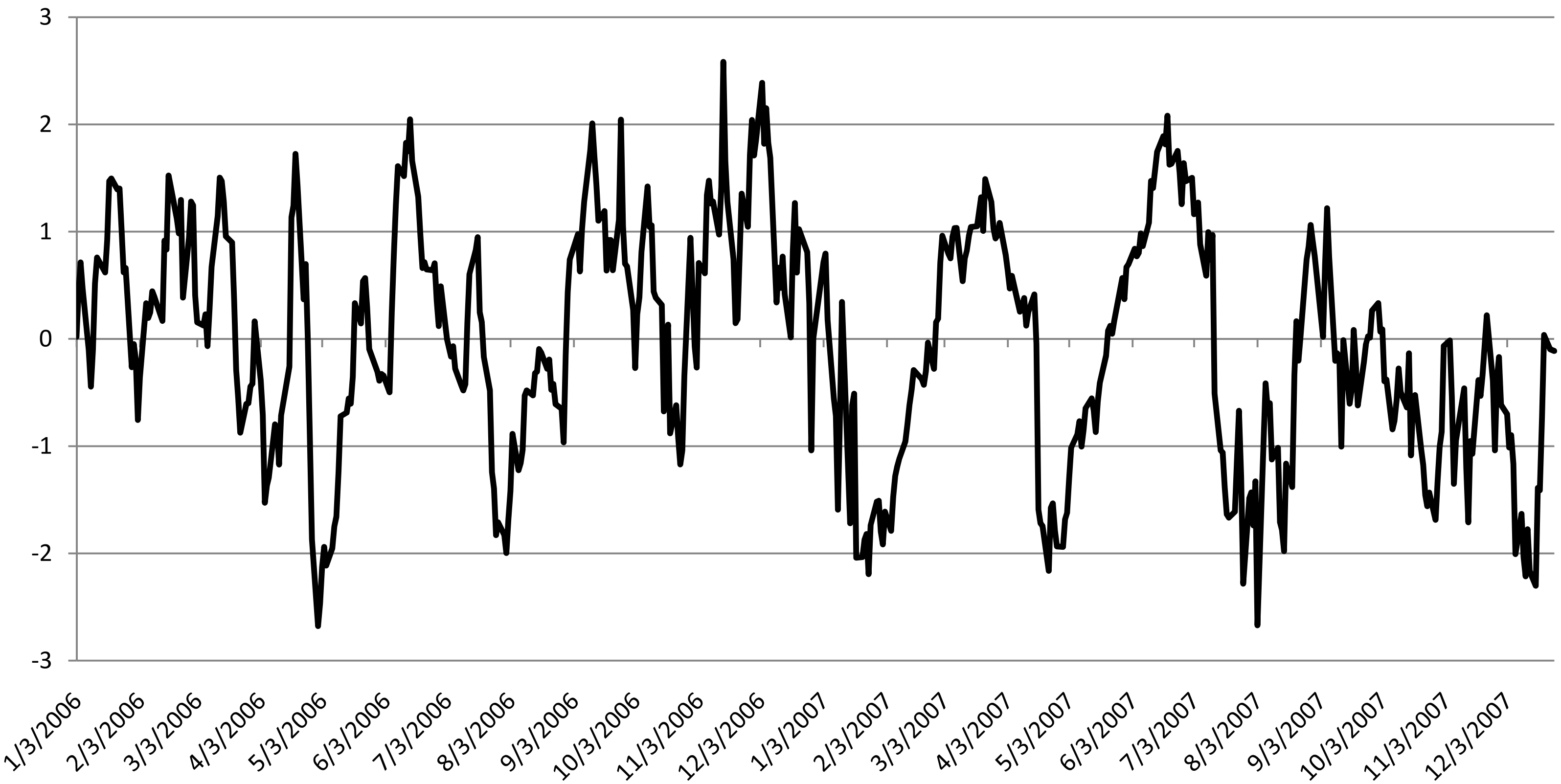
Close long position if $s_i > -0.50$

Close short position if $s_i < +0.50$

Schematic view of mean-reversion trading



S-score of JPM (vs. XLF)

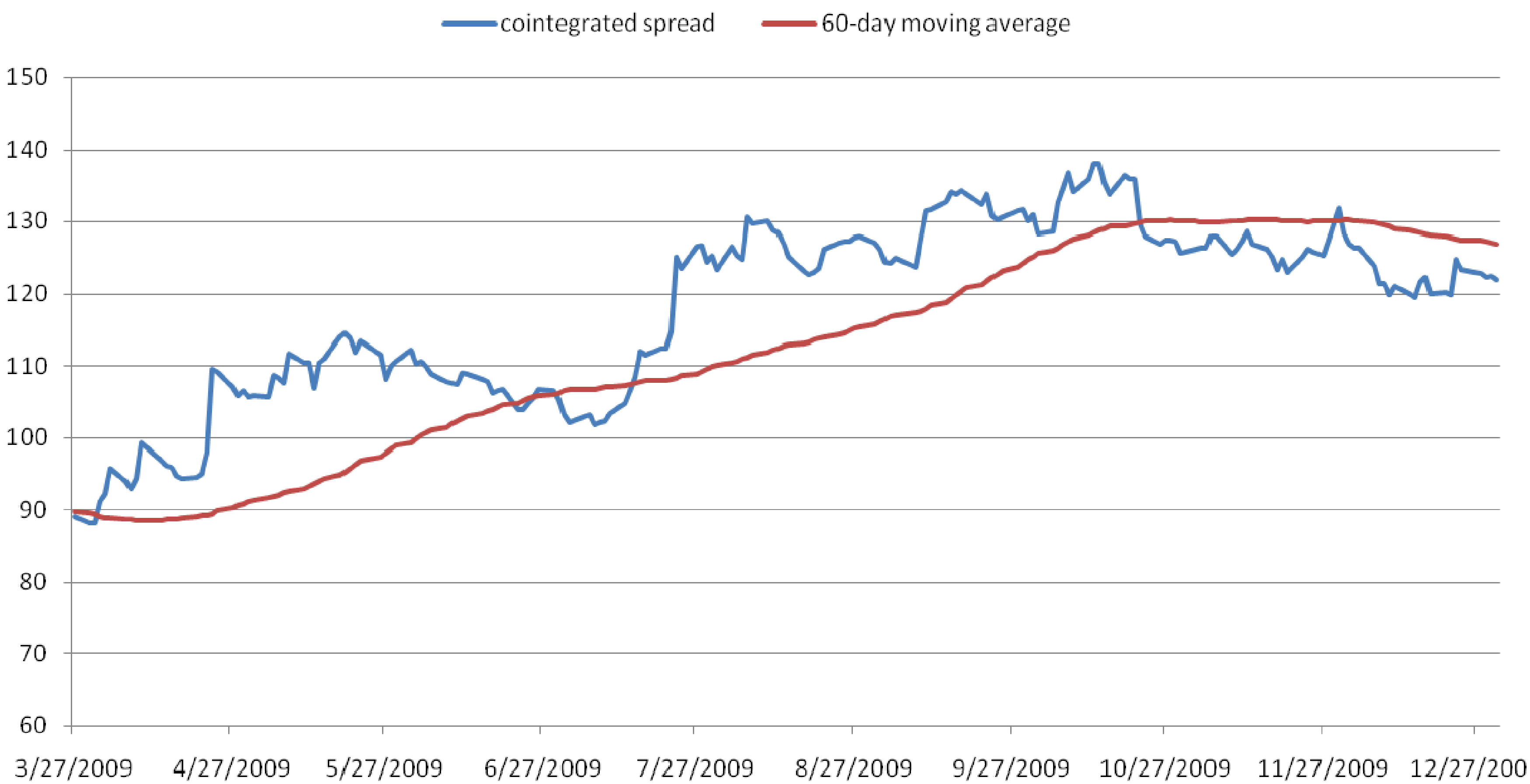


Stock-ETF real trading example : 6 trades in 2009

ticker	trade_date	close_date	days	stock_PNL	etf_PNL	Total_PNL	etf_ticker	size
EBAY	10/9/2009	11/9/2009	16	(3,884.70)	(2,447.11)	(6,331.81)	QQQQ	82,152.96
EBAY	5/26/2009	6/8/2009	9	497.31	(5,278.60)	(4,781.29)	QQQQ	79,388.76
EBAY	5/13/2009	5/14/2009	0	2,973.75	(1,391.58)	1,582.17	QQQQ	79,023.75
EBAY	4/16/2009	4/20/2009	1	(1,981.80)	3,673.72	1,691.92	QQQQ	79,547.25
EBAY	9/23/2009	10/7/2009	9	1,304.16	1,409.00	2,713.16	QQQQ	82,127.76
EBAY	9/8/2009	9/10/2009	1	6,439.61	(2,043.87)	4,395.73	QQQQ	81,613.02

stock_cost	stock_shares	stock_exe_price	etf_cost	etf_shares	etf_exe_price	open_s_score	close_s_score	beta
24.32	3378	23.17	42.43	(2,562.42)	43.39	(2.24)	(0.89)	0.756
17.56	4521	17.67	34.69	(2,559.32)	36.75	(1.84)	(1.00)	0.894
16.21	4875	16.82	33.00	(2,676.12)	33.52	(1.53)	(0.41)	0.895
14.45	5505	14.09	33.35	(3,251.08)	32.22	(1.27)	(0.43)	0.734
23.93	3432	24.31	42.58	(2,471.93)	42.01	(2.35)	0.00	0.780
21.81	3742	23.53	40.62	(2,579.02)	41.41	(2.26)	0.13	0.779

A brief history of the EBAY/QQQQ spread (Beta=0.75)



Trading Time vs. Actual Time

Statistics on equity returns (residuals) can be done

-- in **actual time** (% change/day)

-- in **trading time** (% change per share/day)

Trading time incorporates **volume information**.

In trading-time framework, mean-reverting signals (S-Scores) are

-- **weaker** when volume is heavy

-- **stronger** when volume is light

Trading Time vs. Actual Time, II

Using the daily trading volume, construct a residual process which measures the change in price **per share**

$$\varepsilon = \frac{\Delta S}{S} - \beta \frac{\Delta I}{I}$$ (usual residual)

$$\boxed{\bar{\varepsilon} = \frac{< \Delta V >}{\Delta V}\varepsilon, \quad \Delta V = \text{daily volume} \quad < \Delta V >= \text{average}\,\Delta \text{V}}$$

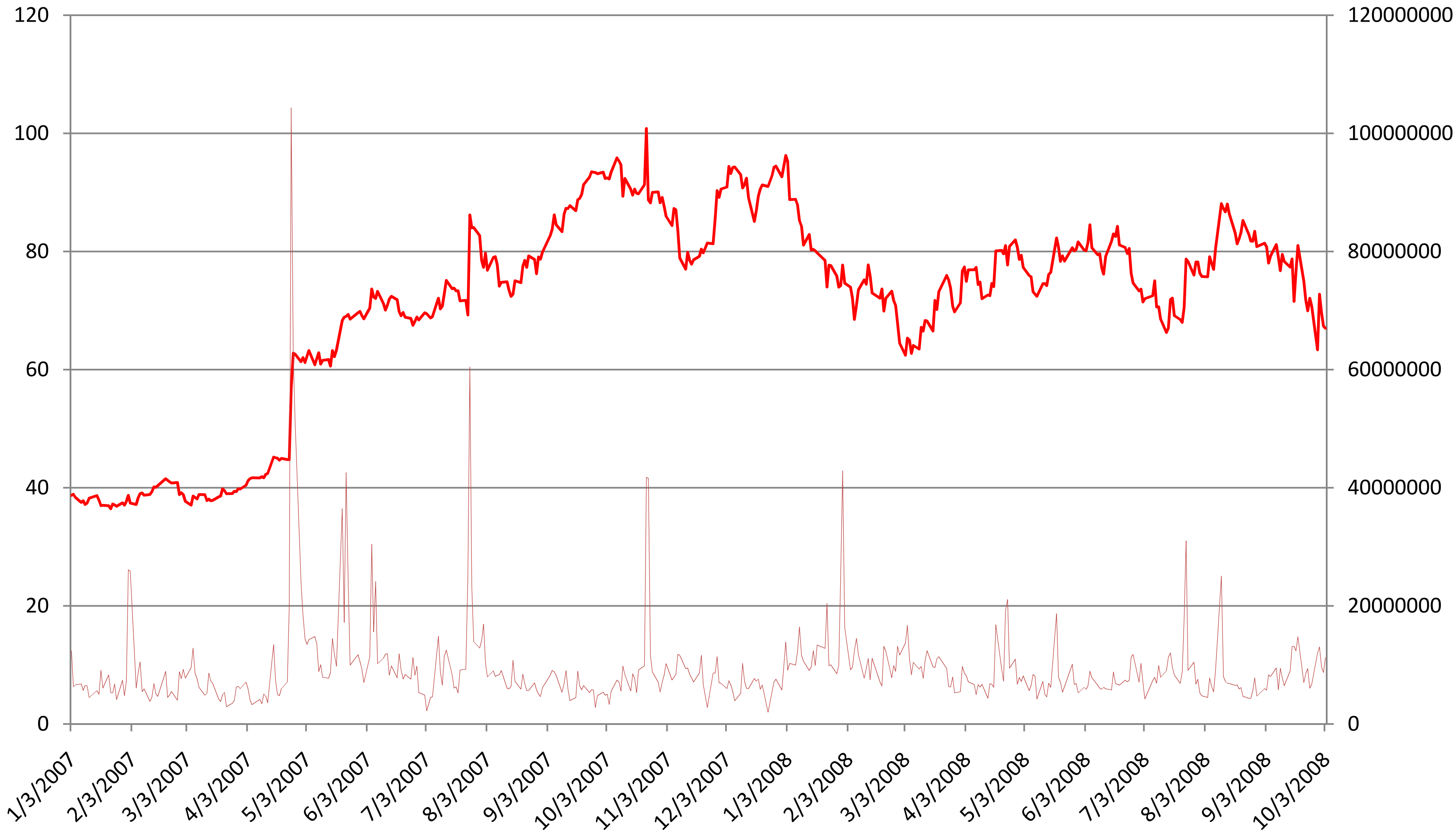
$$Y_t = \sum_{i=1}^{t} \bar{\varepsilon}_i$$

$$dY = \kappa(m - Y)dt + \sigma dW$$

Estimate AR-1 / OU process for the new process Y(t)

This makes deviations on unusually high-volume more likely, so the signal is weaker

Amazon.com Jan 2007-Oct 2008: Avoiding short-selling on large volume



Building a portfolio from ETF-based signals: the PLATA strategy

-- Large, diversified trading universe of equities (~ 1400 names)

-- Select within the trading universe those stocks that have a trading signal (s-score) and open trades

-- All trades consist of stocks paired with ETFs

-- Monitor for closing trades through s-score

-- Monitor for degradation of statistical parameters, stop-losses, etc.

-- Investment per stock ~ 25 bps (~250K per 100MM notional capital)

-- Typical profile 30 to 50 % long / 30 to 50 % short, dollar-neutral.

-- Portfolio-level risk management used to ``vet'' trades.

Portfolio Risk-Management

$Q_i \quad i = 1, \ldots, N$ holdings in stock or ETF i.

$V(Q_1, Q_2, \ldots, Q_N) = \sum_{ij=1}^{N} C_{ij} Q_i Q_j$ daily portfolio variance

C: covariance matrix estimated with 3m window

$\mathbf{Q} = (Q_1, Q_2, \ldots, Q_N)$ position at date T

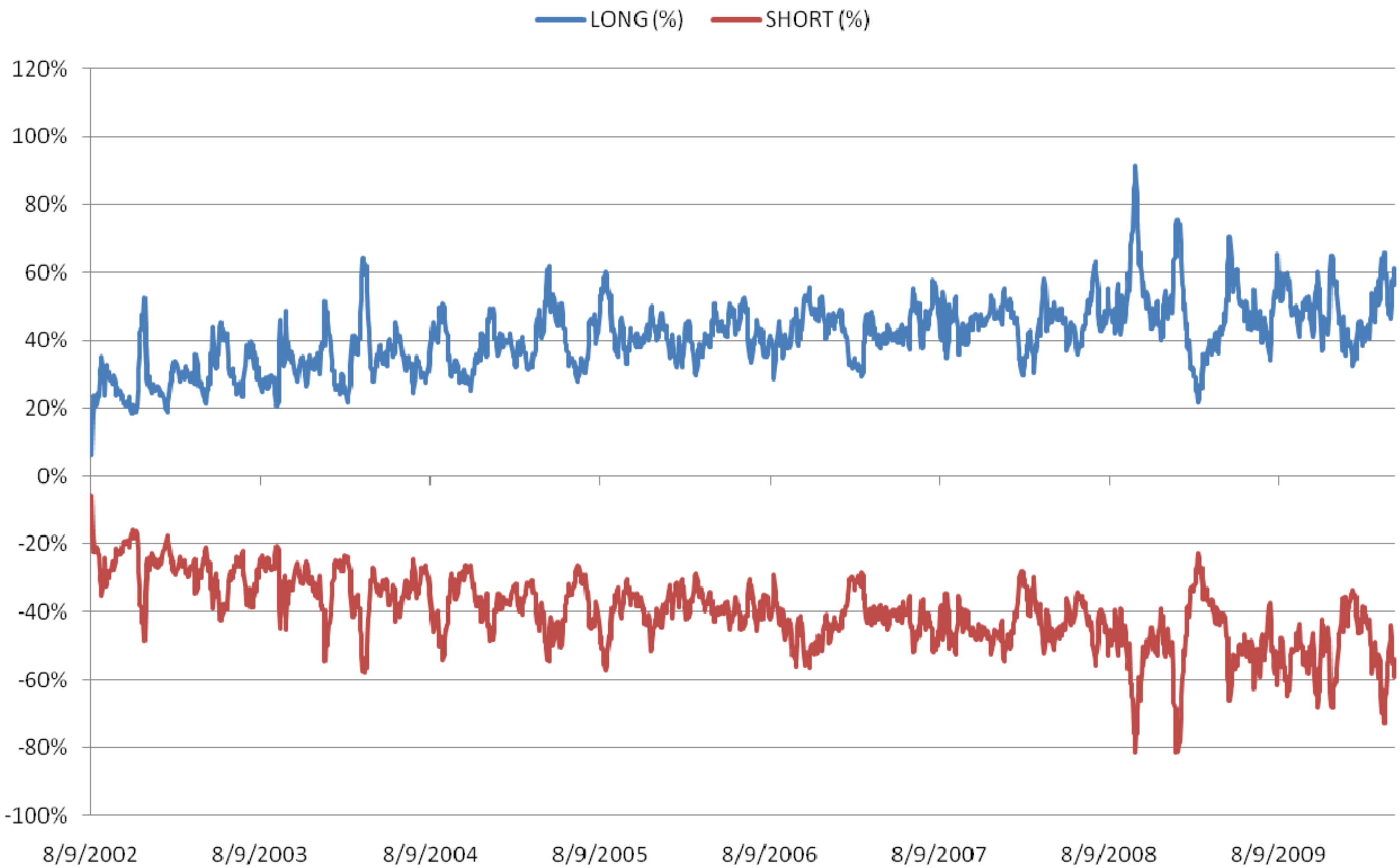
$\mathbf{Q'} = (Q_1', Q_2', \ldots, Q_N')$ target (desired) position date $T+1$

Risk - control algorithm : let ε denote a risk threshold (e.g. 25bps of daily stdev)

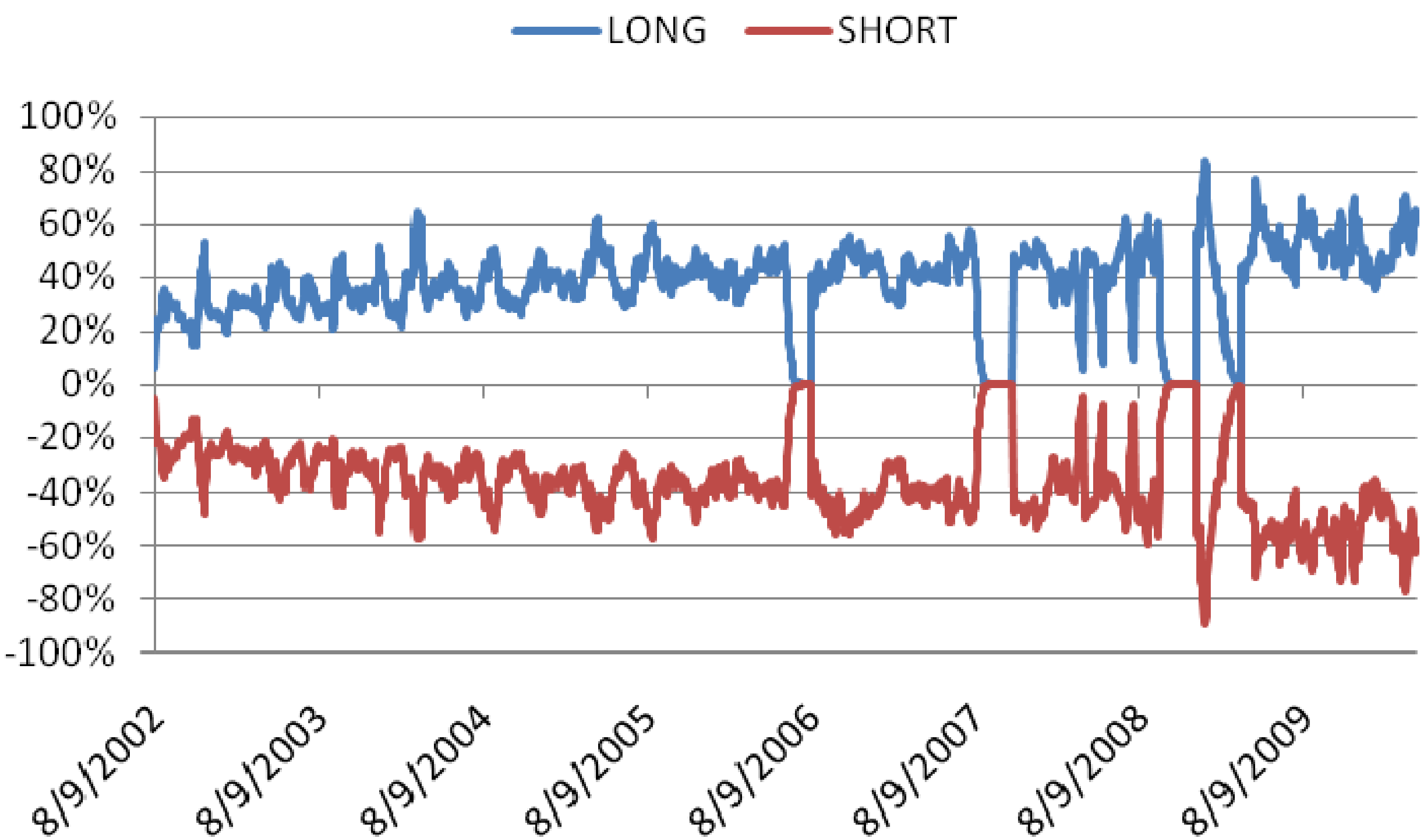
If $V(\mathbf{Q'}) > \varepsilon$ then only execute `closing trades' $\mathbf{Q} \to \mathbf{Q'}$

If $V(\mathbf{Q'}) \leq \varepsilon$ then execute all trades $\mathbf{Q} \to \mathbf{Q'}$

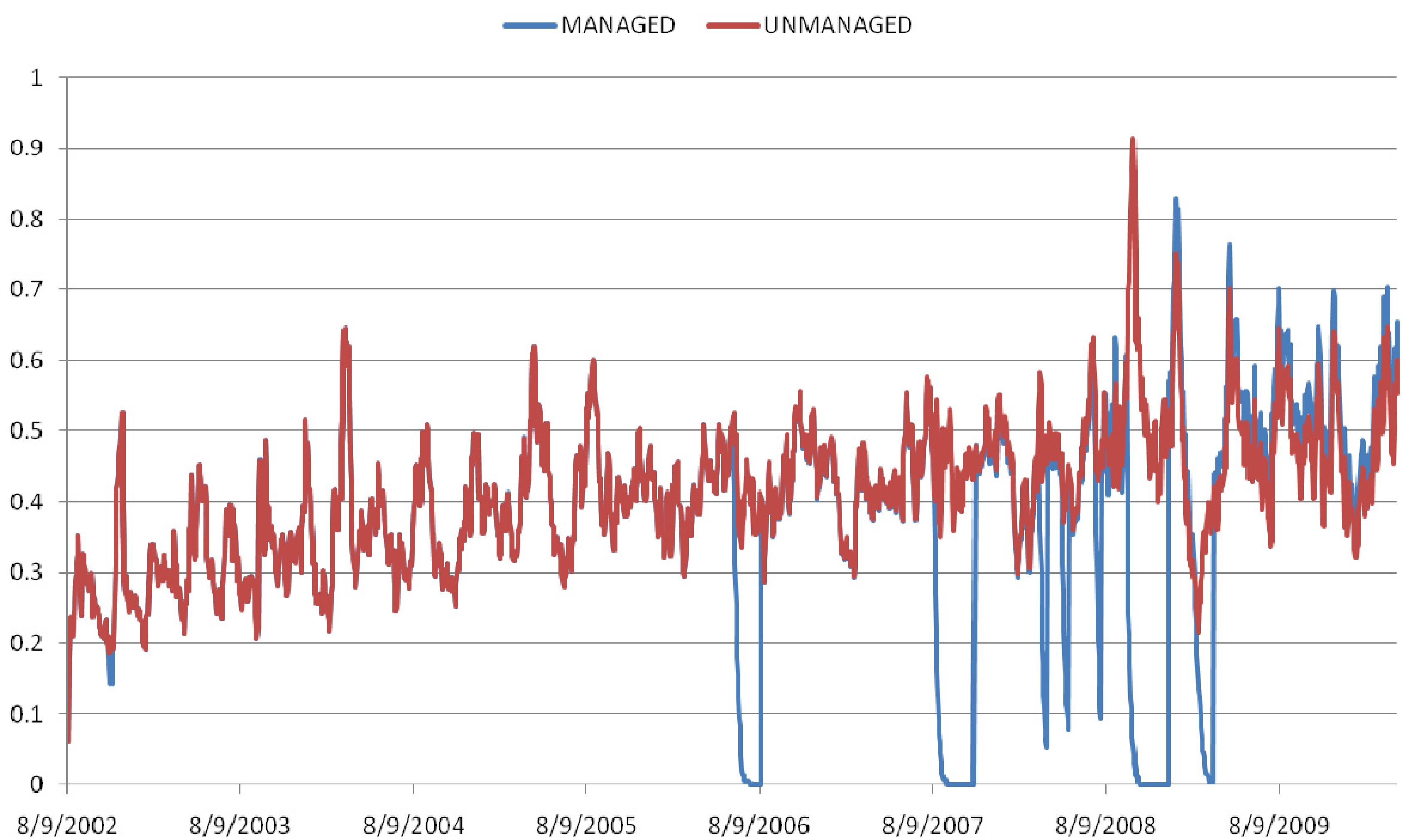
Long and Short positions for unmanaged portfolio (% of account equity)



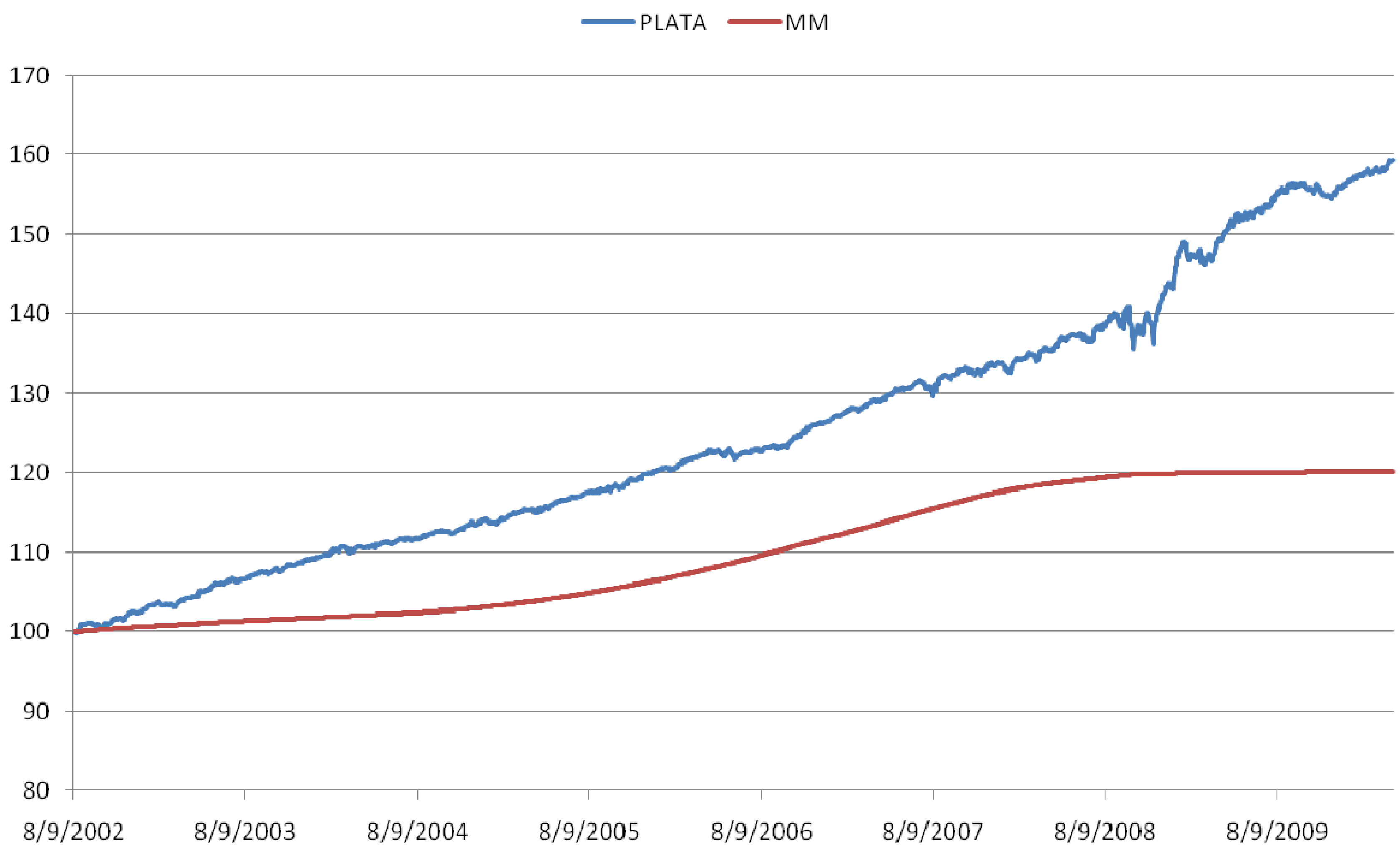
Long/short balances with portfolio risk-management



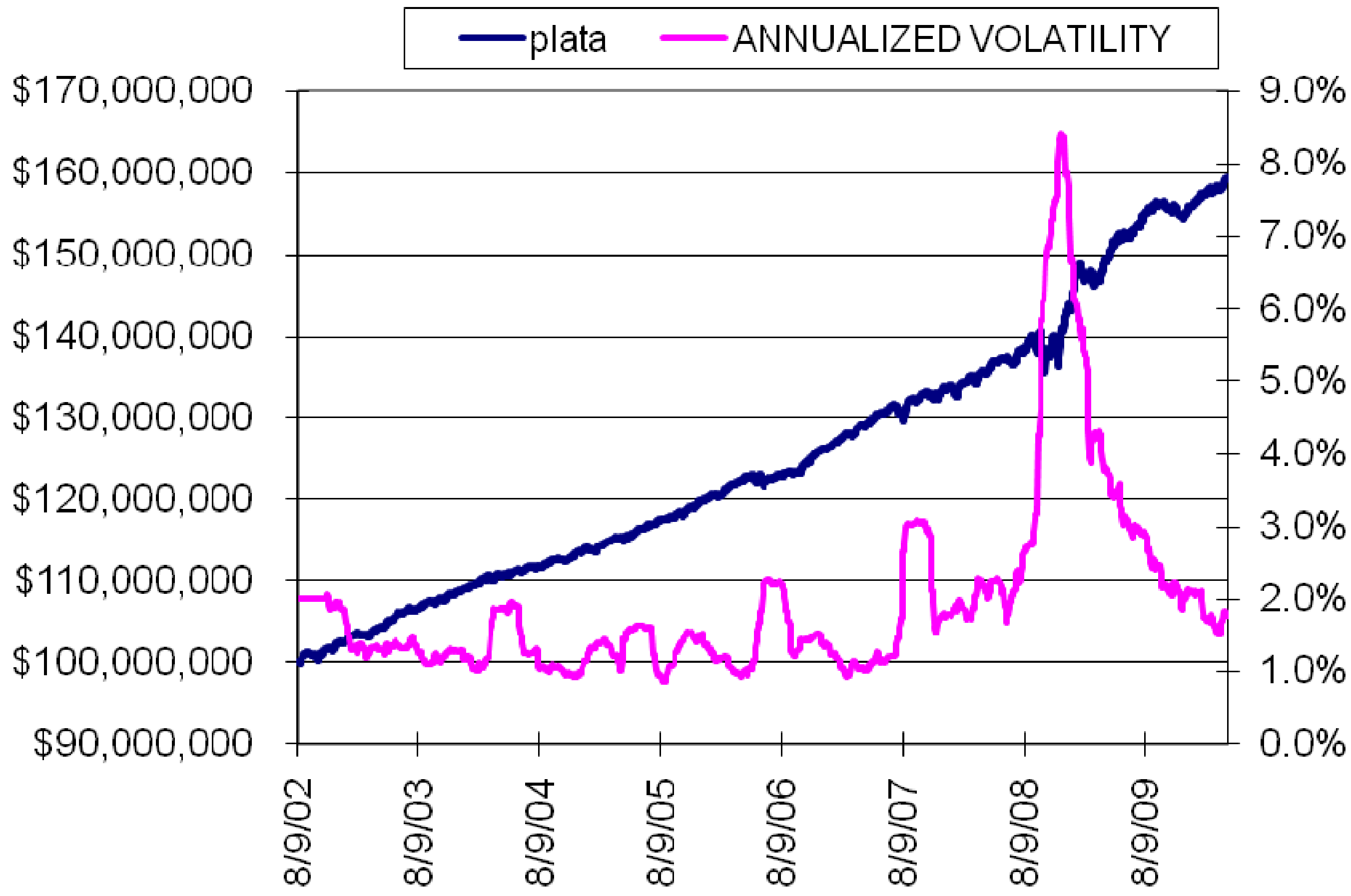
Comparison between Long balances: managed & unmanaged simulations



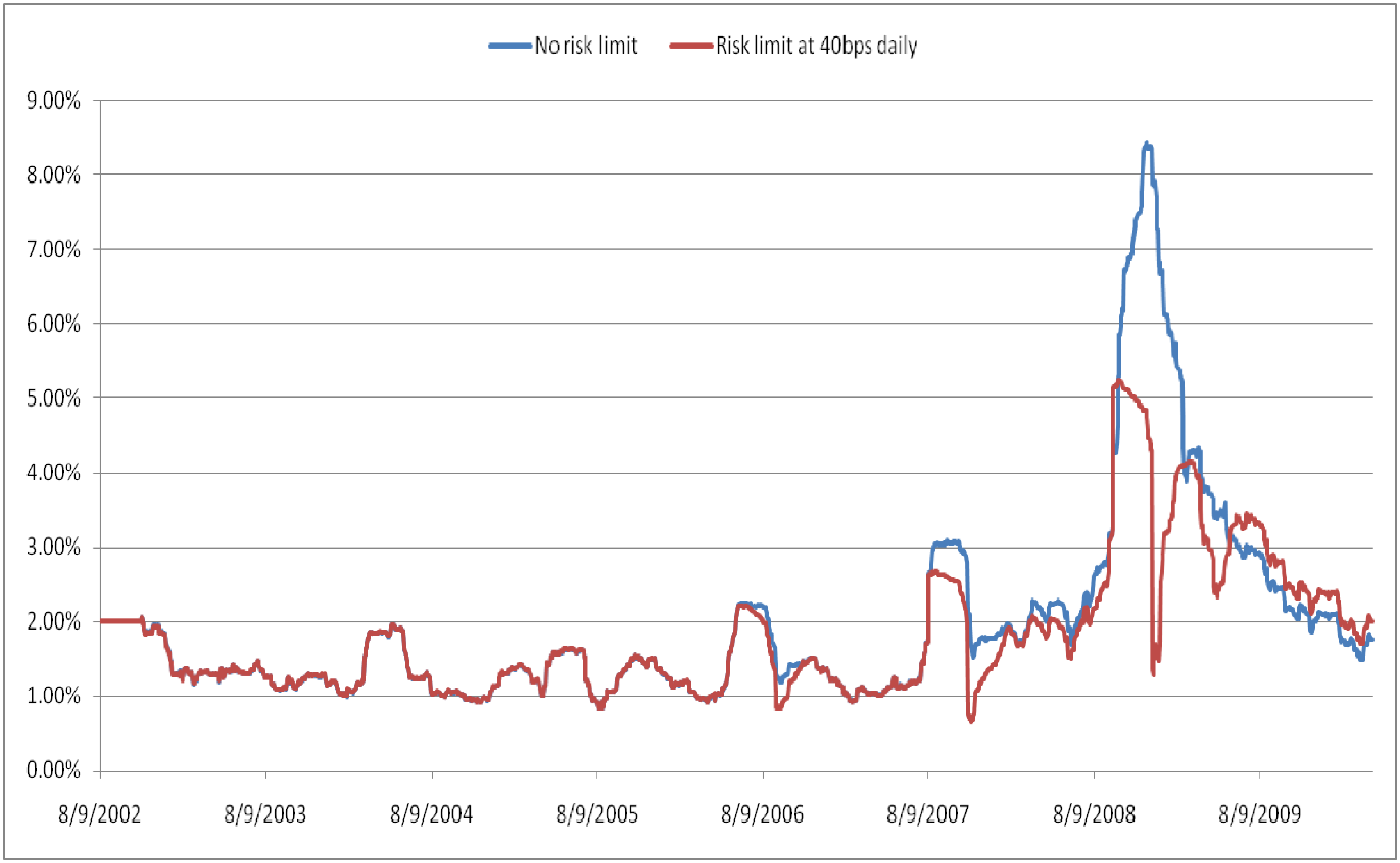
Basic PLATA : 0.25% per stock position
Leverage: 20/20 to 40/40, target daily vol=25 bps



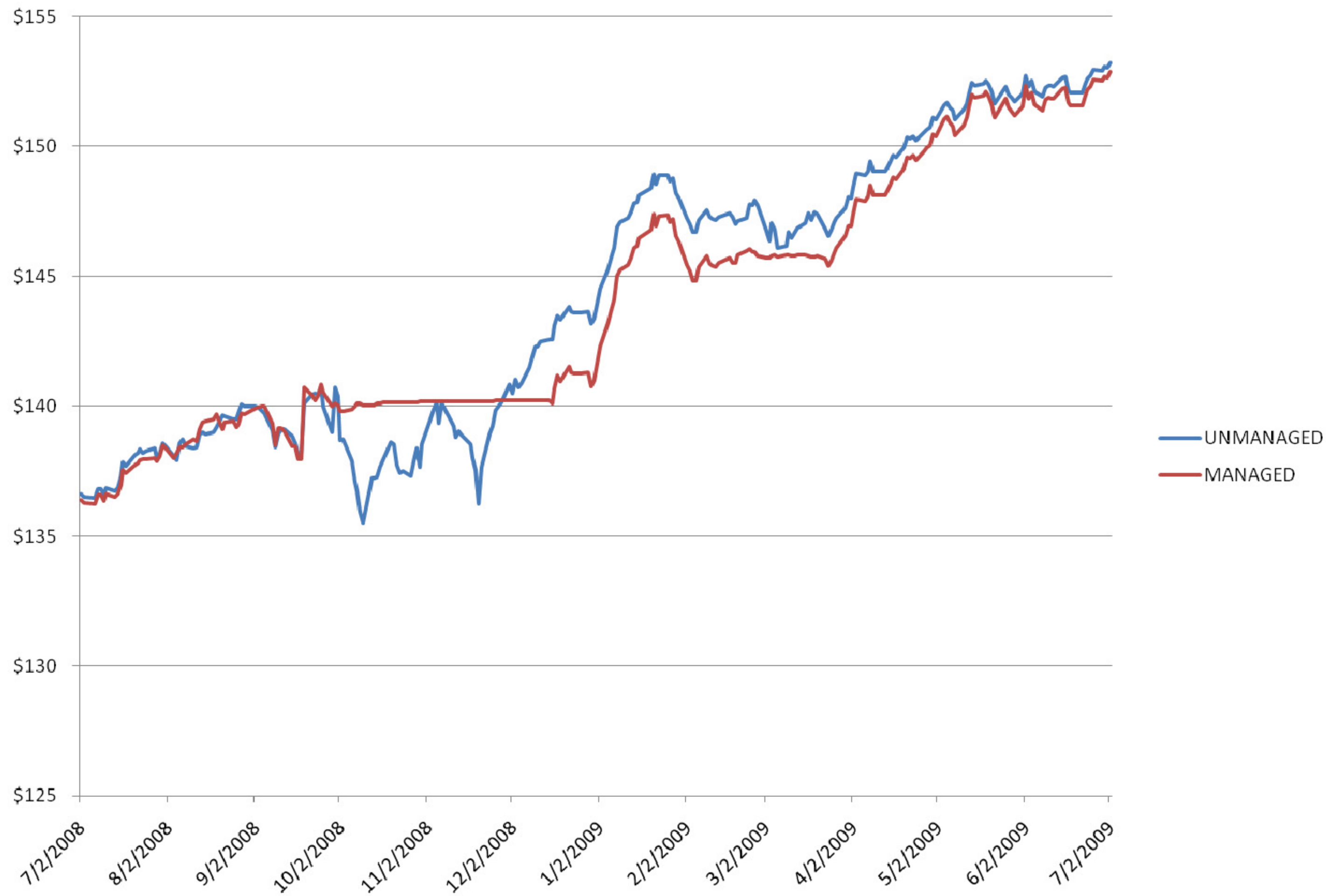
Trailing annualized volatility without portfolio risk management



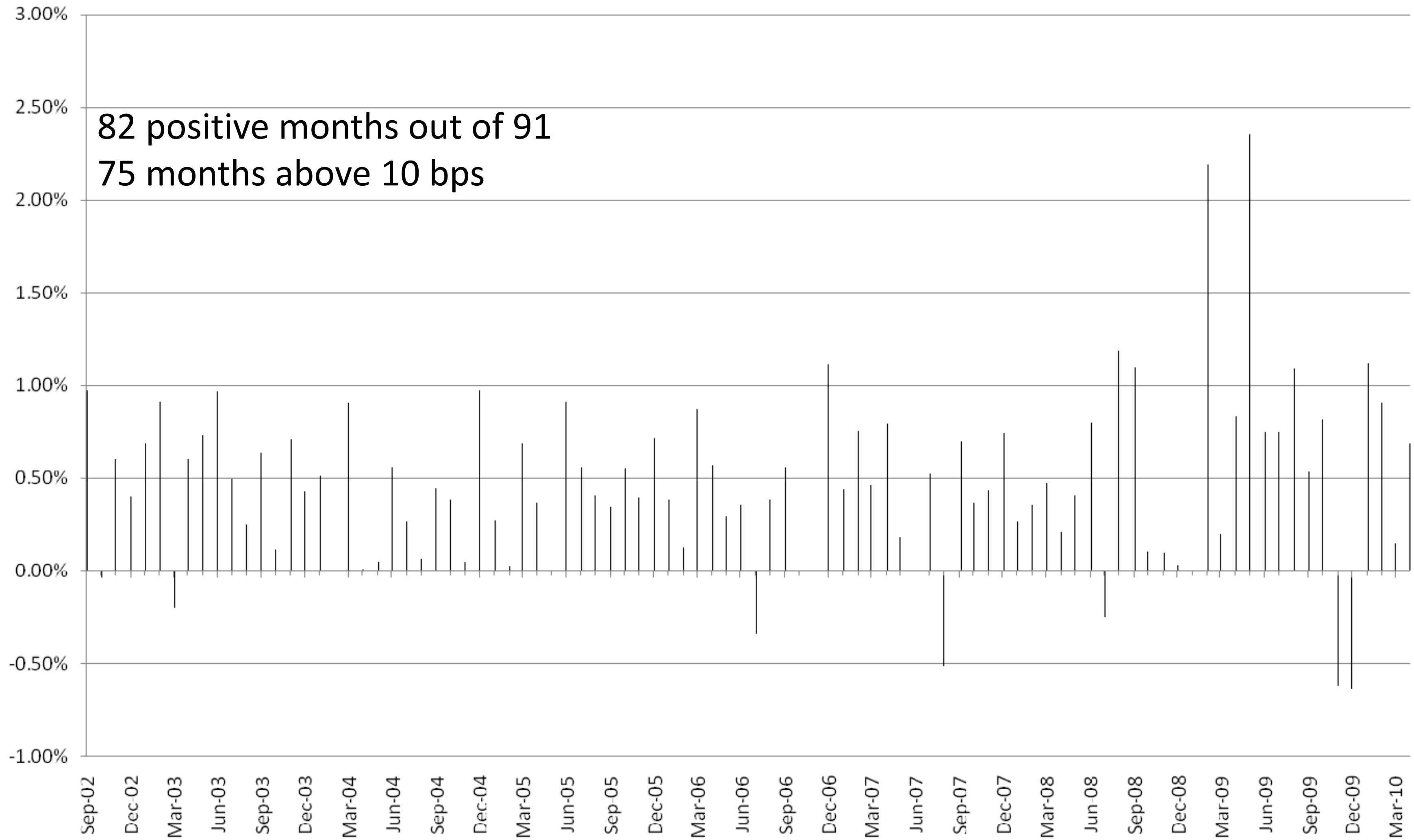
Volatility of PLATA with and without risk limit



Difference between managed risk and unmanaged risk in the Fall of 2008

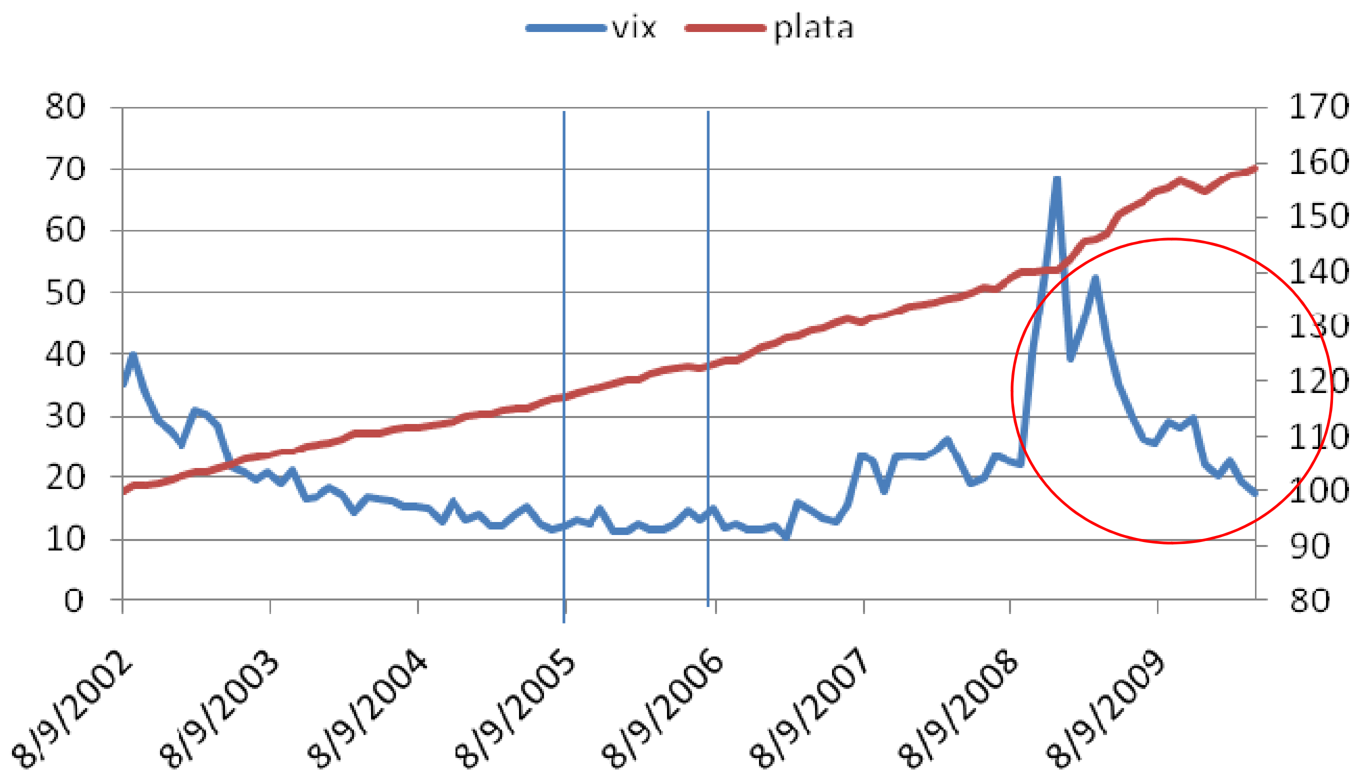


PLATA monthly performance since September 2002



PLATA Monthly Statistics	
Mean	0.50%
Standard Error	0.05%
Median	0.46%
Mode	NA
Standard Deviation	0.48%
Sample Variance	0.00%
Kurtosis	3.01
Skewness	0.75
Range	3%
Minimum	-1%
Maximum	2%
Sum	0.46
Count	91
Largest(5)	1.12%
Smallest(5)	-0.25%
Confidence Level(99.0%)	0.13%

Volatility and Stat Arb (Plata)



PLATA works better in the aftermath of volatility spikes and less well when volatility drops. It is therefore reasonable to blend it with an index strategy

Statistical Arbitrage and 130/30

Indexers: mutual fund managers and long-only managers
Objective: Track (or beat) returns of the overall market or sector
Underlying theory: CAPM, etc.

130/30 Managers: Long 130%, short 30% with periodic revisions of the portfolio
Essentially, a beta strategy with stock picking

Market-neutral managers: Seek returns that are uncorrelated
with the market (alpha)

Long-Short Equity MN: Fundamental Stock Picking with shorting

Statistical Arbitrage: Quantitative long-short MN

SPY+PLATA: a synthetic 130/30 fund

Based on a notional amount of 100 MM:

-- go long 100 MM SPY and

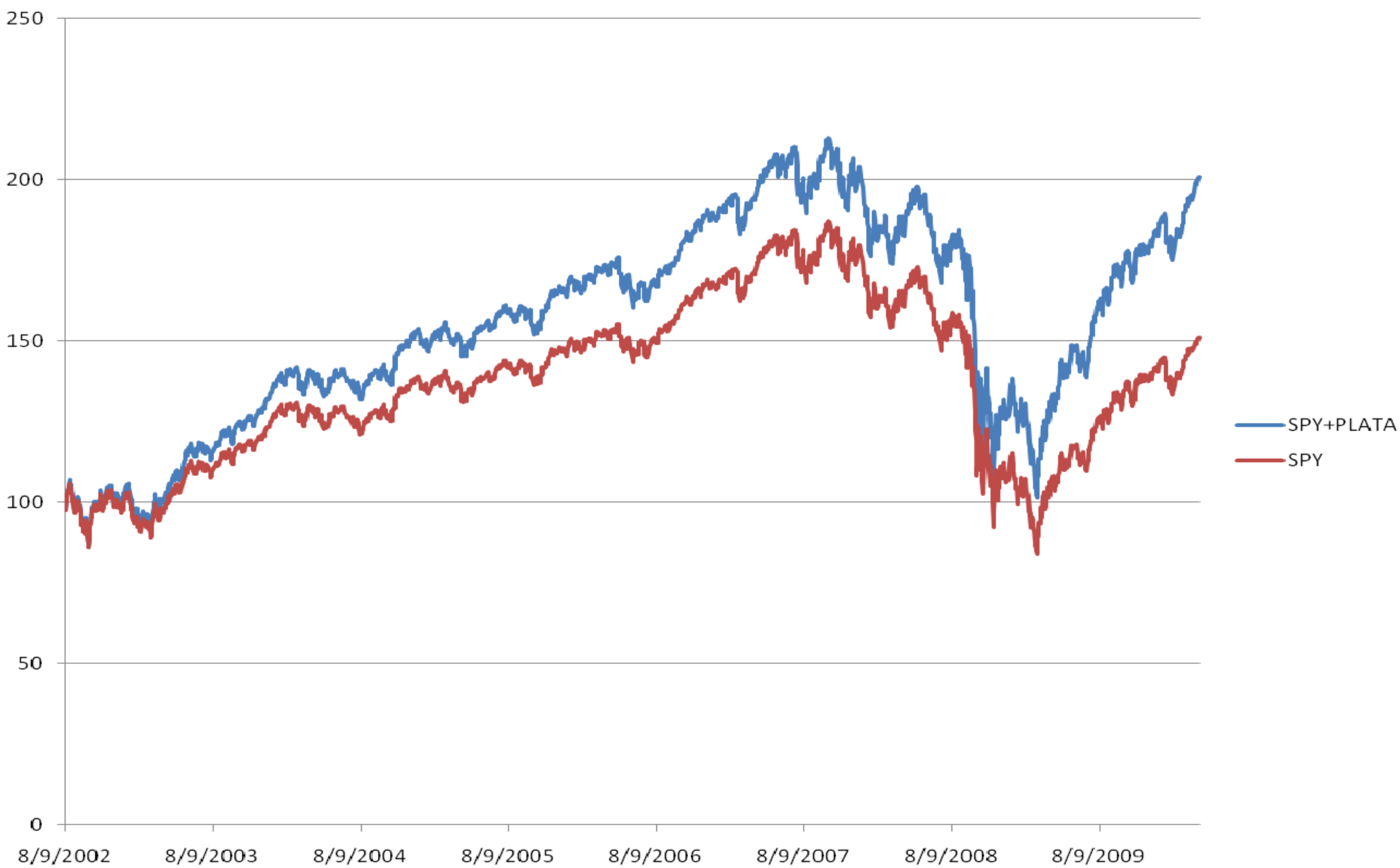
-- enter into a PLATA strategy based on 100MM notional amount
(30 to 50 mm long/ 30 to 50 mm short)

(parameters for PLATA: big universe, 25bps per stock,
target daily stdev of portfolio=25bps)

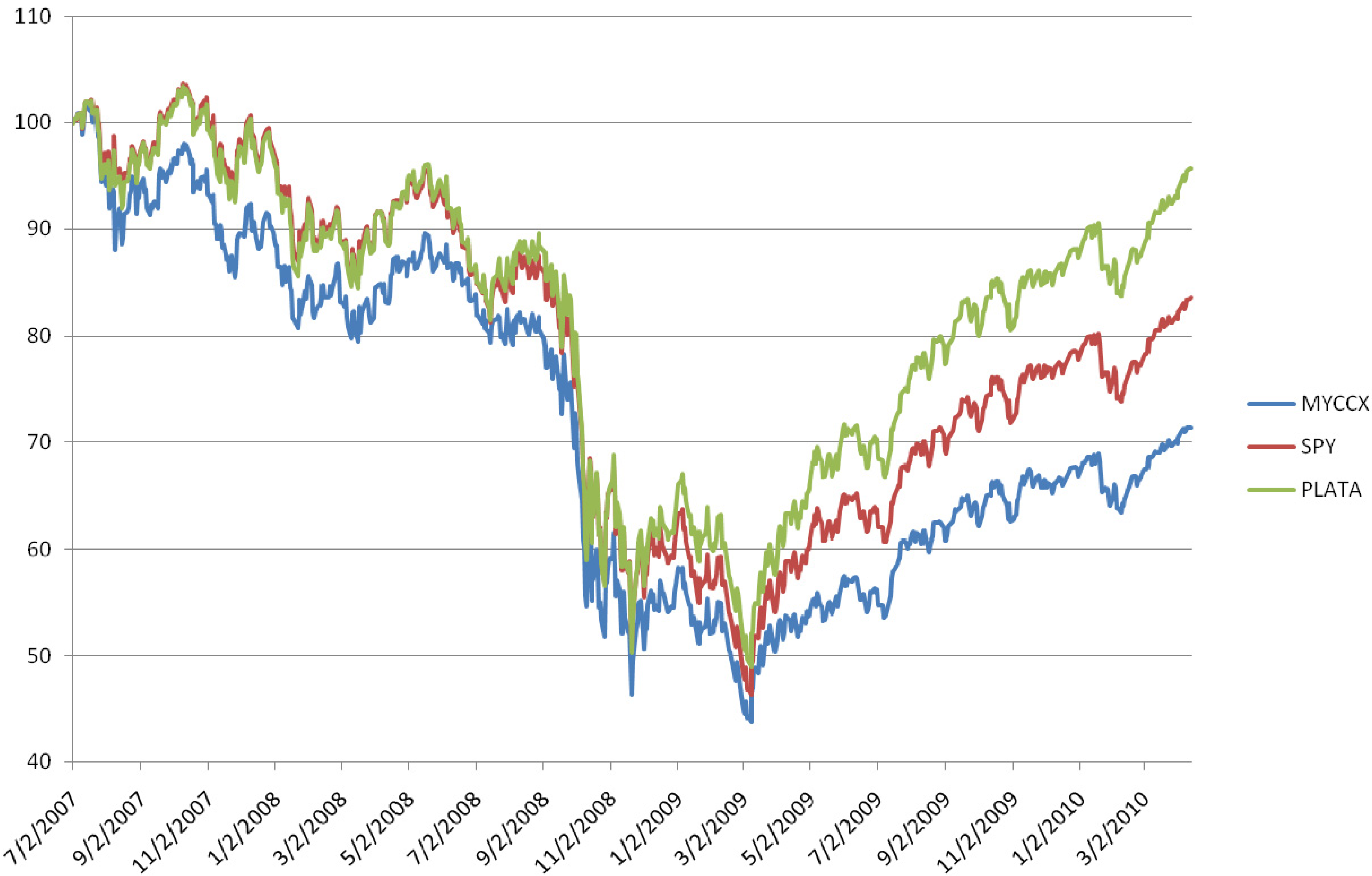
Due to market-neutrality of PLATA, this portfolio looks essentially like a 130/30 to a 150/50 depending on the volatility in the market and the turnover.

-- Proposed fee structure: ~ 1.20% per year

Comparing SPY+PLATA with SPY

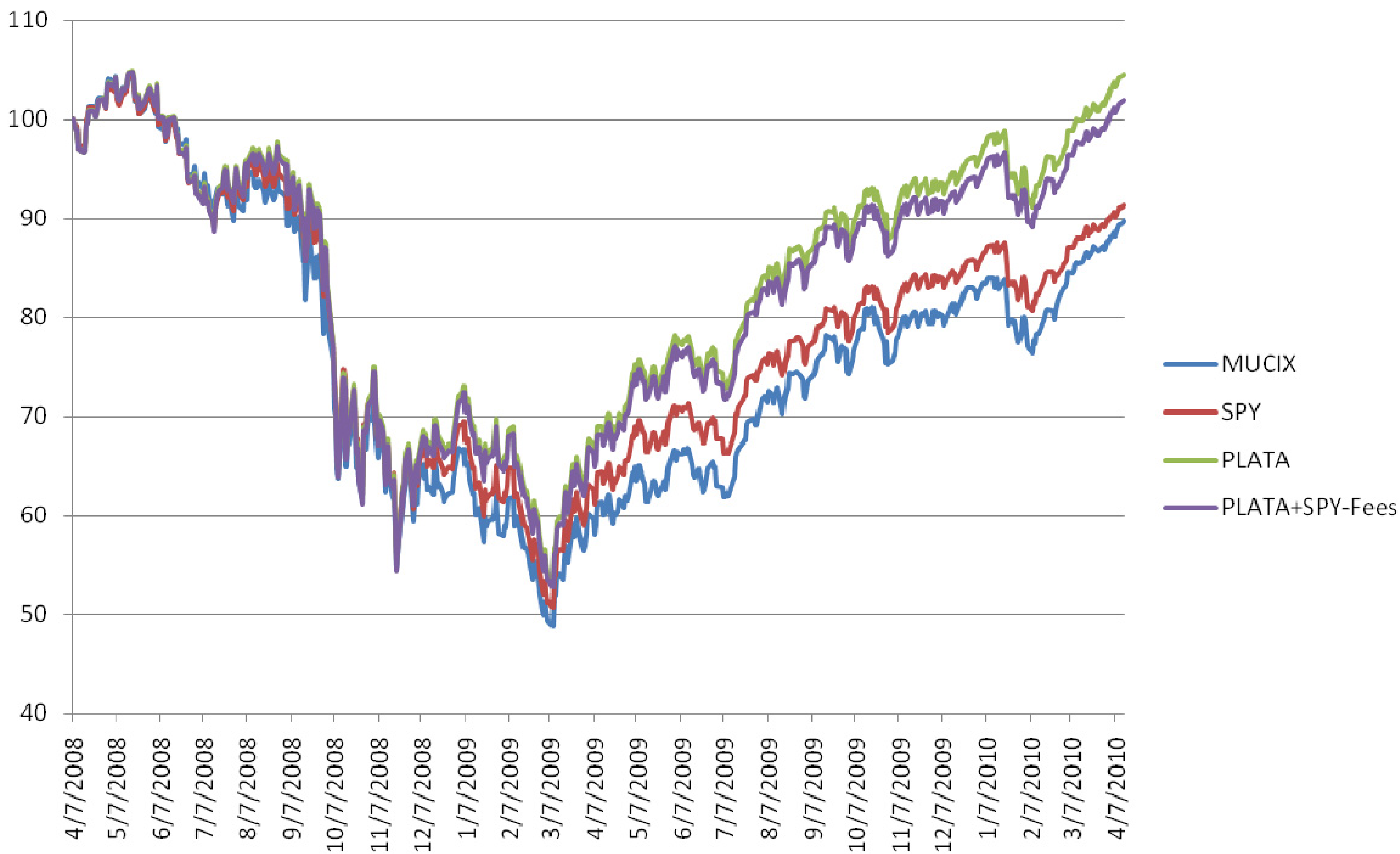


MainStay 130 30 Core C (MYCCX)



Fidelity Advisor Large Cap 130/30 (FITOX, FOATX)

BNY Mellon US Core Equity 130/30 (MUCIX)



CSM: the first 130/30 ETF

-- Proshares launched the first 130/30 ETF in July 2009

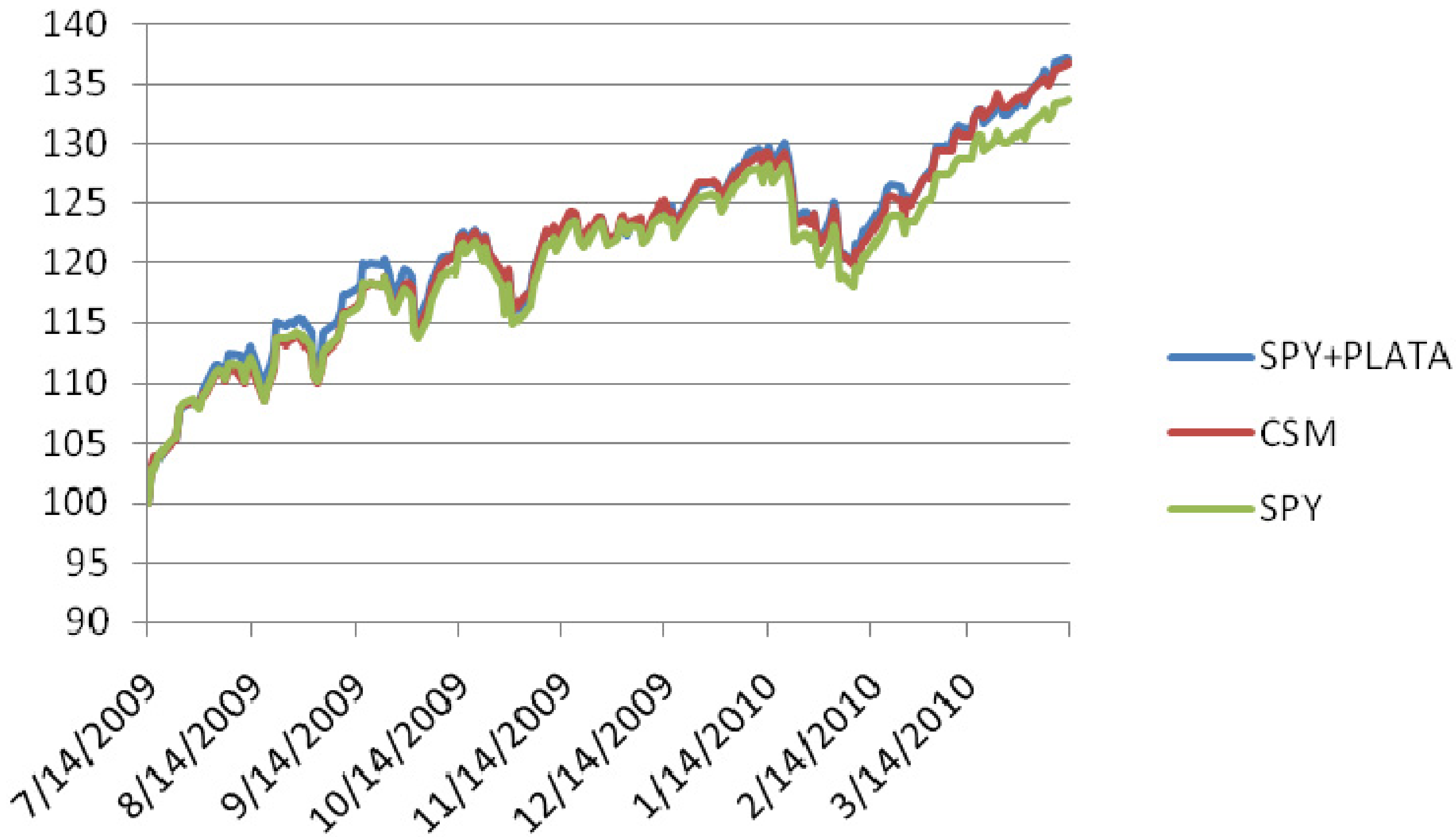
-- Based on the 13030 Large Cap Index constructed by Andrew Lo (MIT) and Panjak Patel (Credit Suisse)

-- Based on ranking stocks in S&P 500 according to 10 quantitative criteria (Book to Value, Momentum, etc)

-- Monthly rebalancings

-- Data available does not include the credit crunch

Comparison of SPY+ PLATA with CSM since inception (7/2009)



Conclusion

Is Statistical Arbitrage ready for the big time?

-- Yes, because it provides a systematic way of picking stocks (long and short) based on objective criteria.

-- Yes, because it is operates in medium frequency with relatively low turnover costs, so it is scalable.

-- Yes, because it can be leveraged an treated as a total-return strategy (*caveat emptor*, however).

-- Yes, because it can be merged with a long-index fund to create a systematic enhanced-indexing fund or quantitative 130/30.

-- Stat arb makes money when the market has high cross-sectional volatility, which is typically when indexing works less well. This is why Stat Arb and indexing should be combined to make a superior yet simple product which can be benchmarked to the S&P 500.