Pairs Trading: Optimizing via Mixed Copula versus Distance Method for S&P 500 Assets

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Pairs Trading is one type of Statistical âĂIJArbitrageâĂİ

- Identify a pair of stocks that move in tandem
- When they diverge
  - short the higher one
  - buy the lower one
- Reverse your positions when the two prices converge $\Rightarrow$ Profit from the reversal in trend

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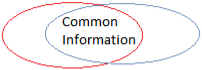
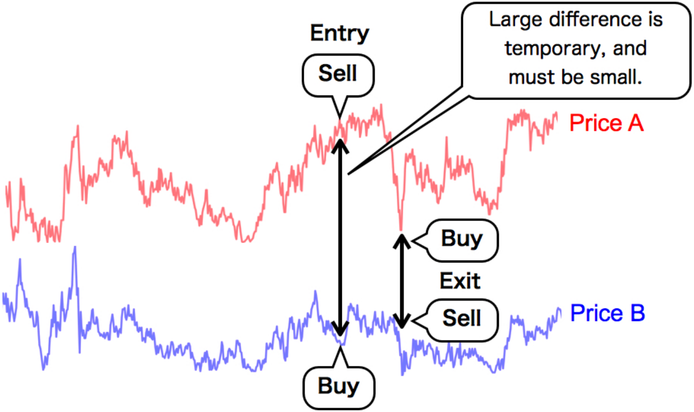
Two-Dimensional Pairs Trading





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- Self-financing.
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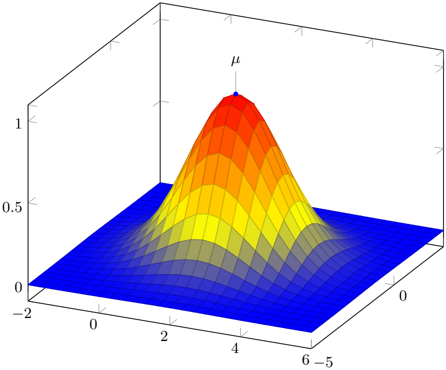
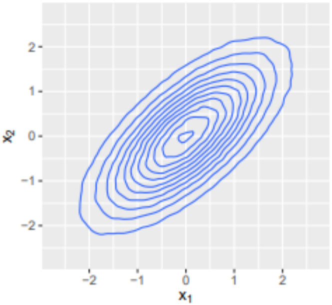
Bivariate Normal Distribution

$$f(x,y)=\frac{\exp\left\{-\frac{1}{2(1-\rho^2)}\left[\left(\frac{x-\mu_x}{\sigma_x}\right)^2-2\rho\left(\frac{x-\mu_x}{\sigma_x}\right)\left(\frac{y-\mu_y}{\sigma_y}\right)+\left(\frac{y-\mu_y}{\sigma_y}\right)^2\right]\right\}}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}}$$





Motivation

- Linear correlation (ρ) fully describes the dependence between securities if the series have joint normal distribution.

- Tail dependence
  - Heavy tails
  - Possibly Asymmetric

- A single distance measure $\Rightarrow$ fail to catch the dynamics of the spread between a pair of securities?
  - We may initiate and close the trades at non-optimal positions.

- Lie and Wu (2013): pairs trading strategy based on 2-dimensional copulas

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Sklar's Theorem (1959)

Theorem 1

Let $X_1, ..., X_d$ *be random variables with distribution functions* $F_1, ..., F_d$*, respectively. Then, there exists an d-copula* C *such that,*

$$F(x_1, ..., x_d) = C(F_1(x_1), ..., F_d(x_d)), \tag{1}$$

for all $\mathbf{x} = (x_1, ..., x_d) \in \mathbb{R}^d$*. If* $F_1, ..., F_d$ *are all continuous, then the function* C *is unique; otherwise* C *is determined only on* $\operatorname{Im} F_1 \times ... \times \operatorname{Im} F_d$*.*

Why should we care about copulas?

- Assuming that $F(\cdot)$ and $C(\cdot)$ are differentiable, by (??) we have

$$\frac{\partial^d F(x_1, ..., x_d)}{\partial x_1 ... \partial x_d} \equiv f(x_1, ..., x_d) = \frac{\partial^d C(F_1(x_1), ..., F_d(x_d))}{\partial x_1 ... \partial x_d} \quad (2)$$

$$= c(u_1, ..., u_d) \prod_{i=1}^{d} f_i(x_i), \quad (3)$$

where $u_i = F_i(x_i)$, $i = 1, ..., d$.

multivariate = "1-dim" (marginals) + "joint" (copula)

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Copula

- Any multivariate distribution can be factored into its purely univariate features (marginal distributions) and its purely "joint" component (copula).
- The copula represents the true interdependence structure of a random variable.

Strategy	Associations Captured	Required Marginal Distributions
Distance	Linear	Gaussian
Copula	Linear and Nonlinear	No assumption

In practical terms, the copula provides an effective tool to monitor and hedge the risks in the markets.

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Distance: Methodology

- Two stages:
- 1. Pairs Formation
- Matching partner: Minimize the sum of squared deviations between normalized prices ⇒ twelve-month (formation) period
- Equivalent to matching on state-prices
- Each day is a different state
- Assumes stationarity
- Assumes a year capture all states
- 2. Pairs Trading: Next 6-month period
- Committed capital
- Sum of payoffs over all pairs in period/ pairs
- Allow 1/per pair and fully invested capital
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Distance

- Trades that do not converge can result in a loss $\Rightarrow$ Open at the end of the trading period?
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Copula: Methodology

- Partial derivative of the copula function gives the conditional distribution function

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\begin{aligned}
P\left(U_1 \leq u_1 \,|U_2 = u_2\,\right) &= \frac{\partial C\left(u_1, u_2\right)}{\partial u_2} = P\left(X_1 \leq x_1 \,|X_2 = x_2\,\right), \\
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\end{aligned}
$$

Xie *et al*. (2014) define a measure to denote the degree of mispricing.

Definition 2

- Let R_t^X and R_t^Y represent the random variables of the daily returns of stocks X and Y on time t, and the realizations of those returns on time t are r_t^X and r_t^Y, we have

$$
MI_{X|Y}^t = P(R_t^X < r_t^X \mid R_t^Y = r_t^Y)
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and

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MI_{Y|X}^t = P(R_t^Y < r_t^Y \mid R_t^X = r_t^X),
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\end{aligned} \tag{4}
$$

- A conditional value of 0.5 $\Rightarrow$ two underlying stocks are considered fairly-valued

Copula: Methodology

- The conditional probabilities, $M_t^{X|Y}$ and $M_t^{Y|X}$: measure the degrees of relative mispricing for a single day.

- Overall degree of relative mispricing (Rad *et al*. (2016)).

- Let $m_{1,t}$ and $m_{2,t}$ be the overall mispricing indexes of stocks X_1 and X_2, defined by $\left(M_t^{X|Y} - 0.5\right)$ and $\left(M_t^{Y|X} - 0.5\right)$, respectively. At beggining of each trading period two cumulative mispriced indexed M_1 and M_2 are set to zero and then evolve for each day through

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M_{1,t} &= M_{1,t-1} + m_{1,t} \\
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- Sensitivity analysis: open a long-short position once one of the cumulative indexes is above 0.05, 0.10, . . ., 0.55 and the other one is below -0.05, -0.10, . . ., -0.55 at the same time
- How many pairs do we use?
  - 5, 10, 15, 20, 25, 30 and 35
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Pairs Implementation: Copula

- Estimate the marginal distributions of returns.

- ARMA(p,q)-GARCH(1,1).

- Estimate the two-dimensional copula model to data that has been transformed to [0,1] margins, i.e.,

$$H\left(r_t^X, r_t^Y\right) = C\left(F_X\left(r_t^X\right), F_Y\left(r_t^Y\right)\right),$$

where H is the joint distribution, r_t^X e r_t^Y are stock returns and C is the copula.

- Gaussian, t, Clayton, Frank, Gumbel.

Mixed copula models to cover a wider range of dependence structures are proposed.

- Archimedean mixture copula consisting of the optimal linear combination of Clayton, Frank and Gumbel copulas.
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Mixed Copula

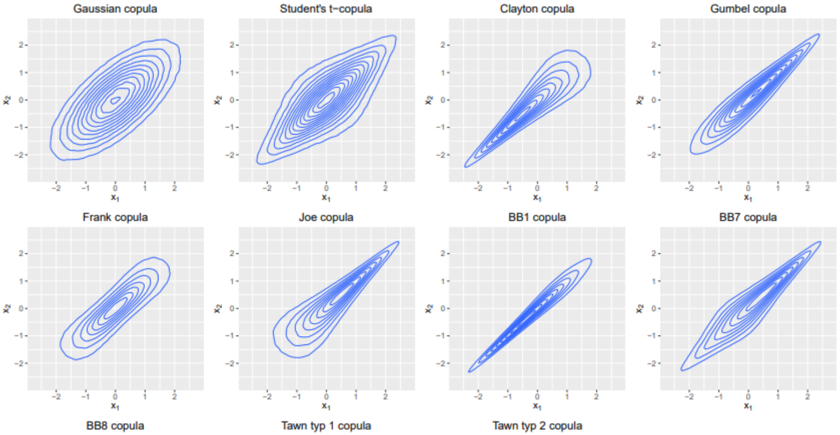
$$\mathcal{C}_{\theta}^{CFG}\left(u_1,u_2\right)=\pi_1\mathcal{C}_{\alpha}^{C}\left(u_1,u_2\right)+\pi_2\mathcal{C}_{\beta}^{F}\left(u_1,u_2\right)+\left(1-\pi_1-\pi_2\right)\mathcal{C}_{\delta}^{G}\left(u_1,u_2\right),$$

and

$$\mathcal{C}_{\xi}^{CtG}\left(u_1,u_2\right)=\pi_1\mathcal{C}_{\alpha}^{C}\left(u_1,u_2\right)+\pi_2\mathcal{C}_{\Sigma,\nu}^{t}\left(u_1,u_2\right)+\left(1-\pi_1-\pi_2\right)\mathcal{C}_{\delta}^{G}\left(u_1,u_2\right),$$

where $\theta=(\alpha,\beta,\delta)'$ are the Clayton, Frank and Gumbel copula (dependence) parameters and $\xi=(\alpha,(\Sigma,\nu),\delta)'$ are the Clayton, t and Gumbel copula parameters, respectively, and π_1, $\pi_2\in[0,1]$.

Tail Dependence



Data

- **Sources** Adjusted closing prices, Fama-French factors
- Cumulative total return index for each stock
- **Universe** All shares that belongs to the S&P 500 market index
- **Dates** July 2nd, 1990 to December 31st, 2015
- **Totals** 1100 stocks during 6426 days

Risk-Return characteristics

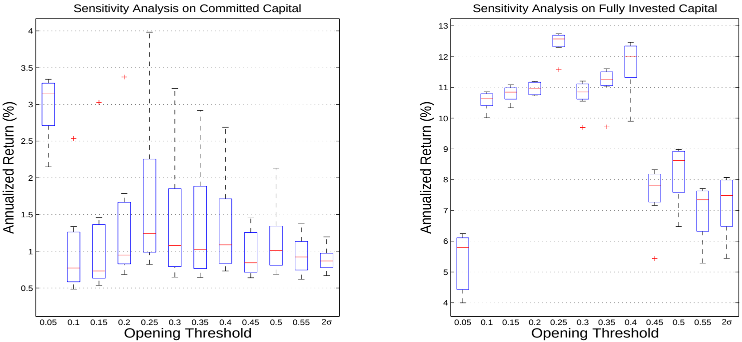


Figure 1: **Annualized returns of pairs trading strategies after costs on committed and fully invested capital**

These boxplots show annualized returns on committed (left) and fully invested (right) capital after transaction cost to different opening thresholds from July 1991 to December 2015 for Top 5 to Top 35 pairs.

Risk-Return characteristics

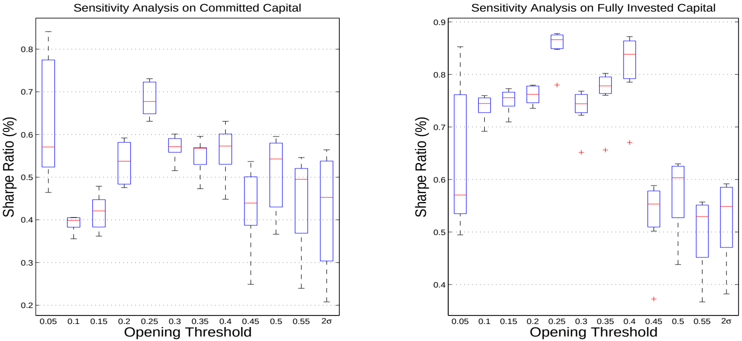


Figure 2: **Sharpe ratio of pairs trading strategies after costs on committed and fully invested capital**

Trading Statistics

Table 1: Trading statistics.

Strategy	Distance	Mixed Copula
	Panel A: Top 5	
Average price deviation trigger for opening pairs	0.0594	0.0665
Total number of pairs opened	352	348
Average number of pairs traded per 6-month	7.18	7.10
Average number of round-trip trades per pair	1.44	1.42
Standard Deviation	1.0128	1.33
Average time pairs are open in days	50.70	37.70
Standard Deviation	39.24	38.93
Median time pairs are open in days	38.5	19
	Panel B: Top20	
Average price deviation trigger for opening pairs	0.0681	0.0821
Total number of pairs opened	1312	749
Average number of pairs traded per 6-month	26.78	15.29
Average number of round-trip trades per pair	1.34	0.76
Standard Deviation	0.99	0.99
Average time pairs are open in days	51.65	23.60
Standard Deviation	39.62	32.90
Median time pairs are open in days	41	9

Trading Statistics

Table 2: Trading statistics.

Strategy	Distance	Mixed Copula
	Panel C: Top 35	
Average price deviation trigger for opening pairs	0.0729	0.0893
Total number of pairs opened	2238	941
Average number of pairs traded per six-month period	45.68	19.20
Average number of round-trip trades per pair	1.30	0.55
Standard Deviation	1.02	0.84
Average time pairs are open in days	52.72	19.35
Standard Deviation	40.48	30.56
Median time pairs are open in days	42	6

Note: Trading statistics for portfolio of top 5, 20 and 35 pairs between July 1991 and December 2015 (49 periods). Pairs are formed over a 12-month period according to a minimum-distance (sum of squared deviations) criterion and then traded over the subsequent 6-month period. Average price deviation trigger for opening a pair is calculated as the price difference divided by the average of the prices.

Trading Performance

Table 3: Excess returns on committed capital of pairs trading strategies on portfolios of Top 5, 20 and 35 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio	t-stat	% of negative trades	MDD1	MDD2
			Return on Committed Capital				
			Panel A - Top 5 pairs				
Distance	2.60	0.31	0.58	1.86*	46.98	6.73	19.62
Mixed Copula	3.98	0.63	1.08	3.49***	41.79	4.36	9.29
			Panel B - Top 20 pairs				
Distance	3.14	0.65	1.13	3.32***	48.02	3.88	9.69
Mixed Copula	1.24	0.64	1.04	3.52***	41.33	2.07	3.43
			Panel C - Top 35 pairs				
Distance	3.12	0.77	1.36	3.92***	47.97	2.70	7.52
Mixed Copula	0.82	0.73	1.19	3.95***	41.31	1.18	1.98
S&P 500	4.36	0.23	0.52	1.79*	47.45	12.42	46.74

Note: Summary statistics of the annualized excess returns, annualized Sharpe and Sortino ratios on portfolios of top 5, 20 and 35 pairs between July 1991 and December 2015 (6,173 observations). The t-statistics are computed using Newey-West standard errors with a six-lag correction. The columns labeled MDD1 and MDD2 compute the largest drawdown in terms of maximum percentage drop between two consecutive days and between two days within a period of maximum six months, respectively.

***, **, * significant at 1%, 5% and 10% levels, respectively.

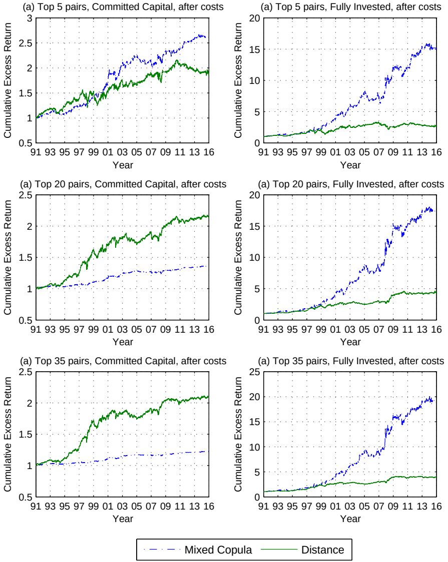
Trading Performance

Table 4: Excess returns on fully invested capital of pairs trading strategies on portfolios of Top 5, 20 and 35 pairs after costs.

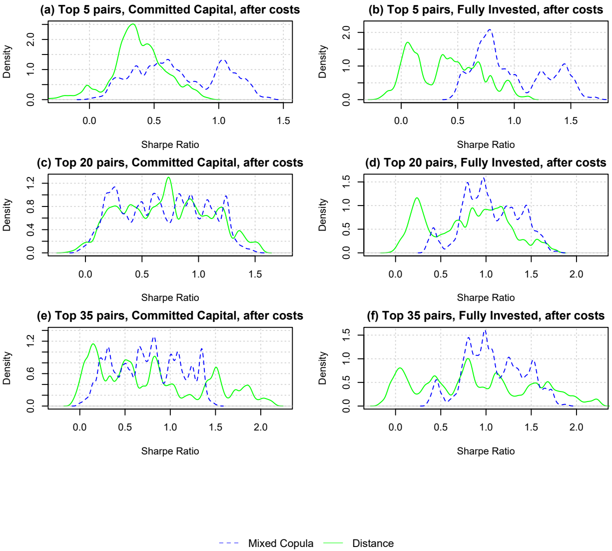
Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio	t-stat	% of negative trades	MDD1	MDD2
			Return on Fully Invested Capital				
			Panel A - Top 5 pairs				
Distance	4.01	0.28	0.57	1.81*	46.98	8.70	38.36
Mixed Copula	11.58	0.78	1.43	4.26***	41.79	9.00	25.68
			Panel B - Top 20 pairs				
Distance	6.07	0.66	1.19	3.55***	48.06	5.43	20.03
Mixed Copula	12.30	0.85	1.54	4.60***	41.31	9.00	25.68
			Panel C - Top 35 pairs				
Distance	5.76	0.76	1.38	4.05***	47.97	4.24	15.07
Mixed Copula	12.73	0.88	1.59	4.73***	41.28	9.00	25.68

***, **, * significant at 1%, 5% and 10% levels, respectively.

Cumulative excess returns of pairs trading strategies after costs



Kernel density estimation of 5-year rolling window Sharpe ratio after costs



Systematic Risk Exposure

Table 5: Monthly risk profile of Top 5 pairs: Fama and French (2016)'s five factors plus Momentum and Long-Term Reversal.

Strategy	Intercept	Rm-Rf	SMB	HML	RMW	CMA	Mom	LRev	R^2	R^2_{adj}
Section 1: Return on Committed Capital										
Distance	0.0025	0.0091	-0.0032	0.0113	0.0003	-0.0029	-0.0107	-0.0084	0.028	0.027
	(1.89)*	(4.22)***	(-0.71)	(2.05)**	(0.25)	(-0.18)	(−4.80)***	(−1.96)**		
Mixed Copula	0.0035	0.0052	-0.0043	0.0039	-0.0035	0.0027	-0.0054	-0.0057	0.015	0.014
	(3.55)***	(3.68)***	(−1.83)*	(1.20)	(-0.99)	(0.63)	(−2.99)***	(-1.57)		
Section 2: Return on Fully Invested Capital										
Distance	0.0040	0.0170	-0.0031	0.0185	0.0049	-0.0018	-0.0161	-0.0150	0.025	0.024
	(1.75)*	(4.88)***	(-0.45)	(2.22)**	(0.76)	(0.05)	(−4.30)***	(−1.97)**		
Mixed Copula	0.0098	0.0148	-0.0084	0.0152	-0.0053	0.0087	-0.0082	-0.0222	0.018	0.017
	(4.17)***	(3.51)***	-1.45	1.6355	-0.60	0.75	(−2.19)**	(−2.08)**		

***, **, * significant at 1%, 5% and 10% levels, respectively.

- Alphas are significantly positive and higher than the raw excess returns by about 2-7 bps per month.
- Only a small part of the excess returns can be attributed to their exposures to the seven risk determinants.

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Conclusions

1. By capturing linear/nonlinear associations and covering a wider range of possible dependencies structures, the mixed copula strategy outperforms the distance method when the number of trading signals is equiparable, especially after the subprime mortgage crisis.

2. We show that the mixed copula pairs trading strategy generates large and significant (at 1%) abnormal returns.

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Extensions

- Copula-based arbitrage for triplets to increase information dependency information and measure relative pricing more comprehensively.

- Vine Copulas (Pair-Copula Constructions)

- Superior flexibility

Extensions

- Machine Learning and AI-based solutions (Man + Machine and NOT Man vs Machine)
- News Sentiment
- Enhances a pairs-trading strategy using an abnormal news volume and sentiment overlay
- Effect of negative news is bigger than positive news and can lead to bigger sell-offs (asymmetry)

Thank you! Questions?

Subperiod Analysis

Table 6: Excess returns on committed capital on portfolios of Top 5 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
	Return on Committed Capital		
	Panel A: 1991-1995		
S&P 500	7.17	0.72	1.30
Mixed Copula	2.66	0.45	0.74
	Panel B: 1996-2000		
S&P 500	10.03	0.51	1.01
Mixed Copula	6.90	1.05	1.77
	Panel C: 2001-2005		
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	6.84	0.83	1.44
	Panel D: 2006:2010		
S&P 500	-1.71	-0.07	0.09
Mixed Copula	1.56	0.24	0.46
	Panel E: 2011:2015		
S&P 500	9.91	0.61	1.09
Mixed Copula	2.01	0.61	1.08

***, **, * significant at 1%, 5% and 10% levels, respectively.

Subperiod Analysis

Table 7: Excess returns on fully invested capital on portfolios of Top 5 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
	Return on Fully Invested Capital		
	Panel A: 1991-1995		
S&P 500	7.17	0.72	1.30
Mixed Copula	7.69	0.56	1.02
	Panel B: 1996-2000		
S&P 500	10.03	0.51	1.01
Mixed Copula	19.61	1.13	1.96
	Panel C: 2001-2005		
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	18.07	1.14	2.07
	Panel D: 2006:2010		
S&P 500	-1.71	-0.07	0.09
Mixed Copula	9.42	0.57	1.16
	Panel E: 2011:2015		
S&P 500	9.91	0.61	1.09
Mixed Copula	3.62	0.37	0.69

***, **, * significant at 1%, 5% and 10% levels, respectively.

Subperiod Analysis

Table 8: Excess returns on committed capital on portfolios of Top 20 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
Return on Committed Capital			
Panel A: 1991-1995			
S&P 500	7.17	0.72	1.30
Mixed Copula	0.93	0.46	0.70
Panel B: 1996-2000			
S&P 500	10.03	0.51	1.01
Mixed Copula	1.67	0.84	1.37
Panel C: 2001-2005			
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	2.43	1.09	1.86
Panel D: 2006:2010			
S&P 500	-1.71	-0.07	0.09
Mixed Copula	0.49	0.22	0.38
Panel E: 2011:2015			
S&P 500	9.91	0.61	1.09
Mixed Copula	0.70	0.77	1.30

***, **, * significant at 1%, 5% and 10% levels, respectively.

Subperiod Analysis

Table 9: Excess returns on fully invested capital on portfolios of Top 20 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
	Return on Fully Invested Capital		
	Panel A: 1991-1995		
S&P 500	7.17	0.72	1.30
Mixed Copula	8.18	0.63	1.10
	Panel B: 1996-2000		
S&P 500	10.03	0.51	1.01
Mixed Copula	18.48	1.08	1.85
	Panel C: 2001-2005		
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	21.07	1.34	2.42
	Panel D: 2006:2010		
S&P 500	-1.71	-0.07	0.09
Mixed Copula	12.09	0.74	1.48
	Panel E: 2011:2015		
S&P 500	9.91	0.61	1.09
Mixed Copula	2.33	0.25	0.49

***, **, * significant at 1%, 5% and 10% levels, respectively.

Subperiod Analysis

Table 10: Excess returns on committed capital on portfolios of Top 35 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
Return on Committed Capital			
Panel A: 1991-1995			
S&P 500	7.17	0.72	1.30
Mixed Copula	0.70	0.60	0.93
Panel B: 1996-2000			
S&P 500	10.03	0.51	1.01
Mixed Copula	0.99	0.84	1.37
Panel C: 2001-2005			
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	1.59	1.23	2.11
Panel D: 2006:2010			
S&P 500	-1.71	-0.07	0.09
Mixed Copula	0.35	0.28	0.46
Panel E: 2011:2015			
S&P 500	9.91	0.61	1.09
Mixed Copula	0.50	0.86	1.56

***, **, * significant at 1%, 5% and 10% levels, respectively.

Subperiod Analysis

Table 11: Excess returns on fully invested capital on portfolios of Top 35 pairs after costs.

Strategy	Mean Return (%)	Sharpe ratio	Sortino ratio
	Return on Fully Invested Capital		
	Panel A: 1991-1995		
S&P 500	7.17	0.72	1.30
Mixed Copula	8.50	0.65	1.14
	Panel B: 1996-2000		
S&P 500	10.03	0.51	1.01
Mixed Copula	19.10	1.12	1.93
	Panel C: 2001-2005		
S&P 500	-2.28	-0.13	-0.06
Mixed Copula	21.81	1.38	2.50
	Panel D: 2006:2010		
S&P 500	-1.71	-0.07	0.09
Mixed Copula	12.39	0.76	1.51
	Panel E: 2011:2015		
S&P 500	9.91	0.61	1.09
Mixed Copula	2.56	0.27	0.53

***, **, * significant at 1%, 5% and 10% levels, respectively.