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DOES PAIR TRADING WORK IN THE KOREAN MARKET?*

We apply statistical arbitrage to conduct pair trading in the Korean stock market. We first construct a multifactor model in 5 selected sectors with the premiums from sector, size, value and momentum portfolios. Sector premium is the excess return of sector indexes over call rate. Second, we investigate whether the residuals from the multifactor model include predictable dynamics. Third, we implement pair trading considering the predictable dynamics of residuals and transaction costs. We control for standard risk factors and transaction costs, yet still find significant trading profit that prior literature cannot explain. Active asset managers can implement our pair trading strategies to enhance their portfolio performance. Our results suggest implications to both academic researchers and practitioners such as active fund managers, risk managers and traders.

Keywords: *pair trading; statistical arbitrage; multifactor model; transaction costs.*

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ЧИ ПРАЦЮЄ ПАРНИЙ ТРЕЙДИНГ НА КОРЕЙСЬКОМУ РИНКУ?

У статті застосовано статистичний арбітраж для проведення парного трейдингу на корейському фондовому ринку. Побудовано багатофакторну модель по 5 обраним секторам з преміями по сектору, розміру, вартості та динамічному портфелю. Премії по сектору — це підвищена прибутковість за секторальним індексом поза ставкою. Досліджено динаміку багатофакторної моделі. Продемонстровано парний трейдинг з урахуванням прогнозованої динаміки нев'язки та операційних витрат. Навіть з урахуванням всіх супутніх ризиків та витрат виявлено суттєвий прибуток від операції, якому немає пояснення в літературі. Менеджери з управління активами можуть використовувати розроблені нами стратегії парного трейдингу для підвищення прибутковості портфелю. Результати дослідження можуть бути корисними як для науковців, так і для практиків — фондових менеджерів, менеджерів ризиків та трейдерів.

Ключові слова: *парний трейдинг; статистичний арбітраж; багатофакторна модель; операційні витрати.*

Форм. 2. Табл. 3. Літ. 18.

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РАБОТАЕТ ЛИ ПАРНЫЙ ТРЕЙДИНГ НА КОРЕЙСКОМ РИНКЕ?

В статье применен статистический арбитраж для проведения парного трейдинга на корейском фондовом рынке. Построена многофакторная модель по 5 выбранным секторам с премиями по сектору, размеру стоимости и динамическому портфелю. Премии по сектору — это повышенная доходность по секторальным индексам сверх ставки. Затем исследована динамика многофакторной модели. Продемонстрирован парный трейдинг с учетом прогнозируемой динамики невязки и операционных издержек. Даже с учетом всех соответствующих рисков и издержек обнаружена существенная прибыль от операций, которой нет объяснения в литературе. Менеджеры по управлению активами могут использовать разработанные нами стратегии парного трейдинга для повышения пробыльности портфеля. Результаты исследования могут быть полезны как

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для научных кругов, так и для практиков — фондовых менеджеров, менеджеров по рискам и трейдеров.

Ключевые слова: *парный трейдинг; статистический арбитраж; многофакторная модель; операционные издержки.*

Introduction. Pair trading is an important strategy. While pair trading has been regarded as a strategy exclusively for sophisticated investors for some time, any investor can implement pair trading nowadays by purchasing various commercial software and packages at rather low prices.

Pair trading is a subset of market neutral strategy to seek absolute performance over cash and to generate stable profit regardless market condition in excess of the compensation to risks and transaction costs. It can be implemented in both fundamental and quantitative research. A quantitative desk of Nunzio Tartaglia in Morgan Stanley firstly designed the strategy and made substantial profit during the 1980s. Since then, pair trading has drawn attention of not only institutional investors, but also retail and individual investors. Recently, people have begun to apply pair trading for hedging purposes as well as for generating excess return.

Pair trading presumes that while the return of an asset is hardly predictable, the ratios or spreads of prices for multiple assets or portfolio are. Pair trading upon quantitative techniques comprises two steps. The first step is to identify two cointegrated assets. Two time series are said to be cointegrated if a linear combination of two series is trend stationary or is stationary after subtracting trend parts. A stochastic process is stationary if its joint probability distribution does not change with time and space. The second step is to set the levels about the price ratio of two assets in order to open or close a pair trading as the price ratio hits the predetermined levels. It is also usual to place loss-cut levels to force closing positions as loss accumulates.

Many papers investigate pair trading. For instance, Gatev et al. (2006) review pair trading comprehensively and conclude that the strategies are profitable. They confirm their argument with a simple contrarian pair trading to generate excess return of 11%. We examine pair trading in auto, semiconductor, health care, bank and information technology (IT) sectors of the Korean market[4]. The average returns from selected pairs are 19% to 50% depending on sectors after accounting for transaction costs. In addition, the risk adjusted excess returns are 18% to 40% after controlling for transaction costs and usual risk sources such as size factor, value factor, market factor and momentum factor. We also show that the trading signal from our pair trading model can explain dispersion of stock returns at least in the Korean market.

In the following sections we briefly review the literature about pair trading and statistical arbitrage. Then we propose our pair trading model based on the multifactor model and mean-reverting process. Next, we analyze the performance of our proposed model. The final section concludes this paper.

Literature. Gatev et al. (2006) examine simple pair trading to generate robust excess return of 11% which they ascribe to fleeting mispricing of substitute assets. Avellaneda and Lee (2010) use exchange-traded fund to construct "tradable" multi-

[4] No paper has so far investigated pair trading at the stock universe in Asian as well as Korean markets. Given the size of the Korean market and the popularity of pair trading, this lack of relevant literature requires serious investigation.

factor model and collect residuals to model them with the Ornstein-Uhlenbeck process. They generate Sharp ratio 1.1 and 1.51 respectively without and with trading volume considered.

More broadly, the popular framework for pair trading is to identify and exploit statistical arbitrage opportunities while fundamental stock analysts often suggest pair trading based on their buy and sell recommendations. Bondarenko (2003) defines statistical arbitrage opportunity as "(i) the expected payoff is positive, and (ii) the conditional expected payoff in each final state of the economy is nonnegative." He shows that statistical arbitrage can generate negative payoffs if the average payoff in each final state is nonnegative. Imposing no opportunity for statistical arbitrage implies new restriction on the dynamics of securities prices. Fajardo and Lacerda (2010) extend Bondarenko (2003) to derive modified versions of the fundamental theorem of asset pricing.

Many empirical papers find statistical arbitrage opportunities do exist. Statistical arbitrage upon momentum and value trading are profitable after accounting for transaction costs, the influence of small stocks, margin requirements, liquidity buffers for the marking-to-market of short-sales, and higher borrowing rates (Hogan et al., 2004). Jarrow et al. (2005) extends Hogan et al. (2004) to find that statistical arbitrage strategies upon stock momentum, value, liquidity and industry momentum generate excess returns over half the time and also proposes efficient trading strategies.

Statistical arbitrage is also useful to optimize portfolios. Alexander and Dimitriu (2005) compare two methods of portfolio optimization – tracking-error variance minimization and cointegration-optimal strategy. While tracking-error variance minimization is the standard in the industry, cointegration-optimal strategy implies superior statistical arbitrage. Profitable market making can be also regarded as a type of statistical arbitrage. For instance, Fernholz and Maguire (2007) show that simple statistical arbitrage techniques similar to market making produce large excess performance.

Statistical arbitrage trading has employed many creative approaches. Some recent statistical arbitrage techniques include genetic programming (Saks and Maringer, 2008), flexible least squares methods isomorphic to Kalman filter (Montana et al., 2009), Almgren-Chriss framework (Lehalle, 2009), Gaussian linear state-space processes with time dependency at high frequency data (Triantafyllopoulos and Montana, 2009).

Outside academia, many practitioners have written about pair trading techniques and statistical arbitrage. Vidyamurthy (2004) is a nice introduction info pair trading and statistical arbitrage. Other books include Whistler (2004), Stokes (2004), Pole (2007) and Kaufman (2011).

Trading signals. In this section, we propose our pair trading model based on the multifactor model and a mean-reverting process of regression residuals. A multifactor model describes a stock (i)'s return at time t ($r_{i,t}$) as:

$$r_{i,t} = \beta_i' \cdot F_t + \varepsilon_{i,t}.$$

β_i is vector of factor loadings, F_t is vector of factor at time t, and $\varepsilon_{i,t}$ is idiosyncratic error for stock i at time t. In line with the prior research about pair trading (Miller et al., 1994; Whistler, 2006; Gatev et al., 2006; Pole, 2007; Avellaneda and

Lee, 2010), we model the idiosyncratic error term with mean-reverting AR (1) process, which is equivalent to Ornstein-Uhlembeck process.

$$\varepsilon_{i,t} = \rho_0 + \rho\varepsilon_{i,t} + u_{i,t}.$$

ρ_0 is a drift term, often called alpha and tends to be insignificant in practice. $k = -log\rho > 0$ denotes the speed of mean reversion. $\tau = 1/k$ represents the periods of converging to the mean of the process. $u_{i,t}$ is white noise distributed with mean 0 and standard deviation σ_u. We regard such mean-reverting $\varepsilon_{i,t}$ as our investment signal for a stock i at time t.

If this mean-reverting process is present and significant enough, investors would be able to generate excess return by taking long- and short- position when the signal climbs up to the first high signal and drops to the first low signal respectively; and by closing the long and short position when the signal drops to the second high signal and climes up to the second low signal respectively. In practice, traders additionally impose the level for loss cut ex-ante such that they force closing long and short positions when the signal climbs to very high or drops to very low signals respectively. The levels for opening and closing pair trading can be dynamic contingent on selected macroeconomic, fundamental or technical variables.

In sum, our pair trading matches a stock return with standard risk factors assuming the return and risk factors are highly correlated, which leads to correlation between stocks in the same sector by chain reasoning. We pick up the opportunities arising from significant divergence between the return and risk factors. Our pair trading style is a kind of statistical arbitrage because we rely on technical analysis to identify statistical mispricing instead of fundamental research.

Specification and data. We apply a four-factor model to estimate the process: the vector of systematic factors (Ft) includes the premiums about sector, value, size, and momentum premium. This setting is almost identical to standard risk models which contain the Fama-French 3 factors and momentum factor.

Sector premium is the difference between sector return and risk free rate and is used instead of usual market premium (market return minus risk free rate) since sector index can explain the return dynamics of its constituents better than market portfolio. To compute sector returns, we use Korean exchange (KRX) sector indices because: 1) it is the most updated sector index and 2) it contains relatively small number of liquid stocks which make it possible to extract systematic risk of individual stocks effectively, and 3) currently available sector ETF's traded in the exchange all replicate the movements of these indices.

KRX publishes 17 KRX sector indices[5]. We choose 5 sectors – auto, semiconductor, health care, bank, and information technology – considering their importance for Korean economy, the length of time series and the number and liquidity of its constituents. The 5 sectors include 100 stocks and 1,516 data points. The stocks are all liquid and of large firms. This makes our trading strategy implementable for even passive fund managers to tilt their portfolios toward our pairs. We use data from January 2005 to January 2011. The estimation period is 60 days. We update the signal on the daily basis via moving window by 1 day. Table 1 describes summary statistics about the sector indices.

[5] http://eng.krx.co.kr/m1/m1_4/m1_4_2/m1_4_2_6/UHPENG01004_02_06.html.

Table 1. **Summary statistics about sector indices**

KRX sector indices	Daily return	Standard deviation	Number of Stocks	Daily return Correlation				
				Auto	Semi-conductor	Health Care	Bank	IT
Auto	0.099%	1.98%	20	1	0.67	0.42	0.54	0.71
Semiconductor	0.101%	1.99%	20		1	0.50	0.53	0.91
Health Care	0.075%	1.63%	10			1	0.35	0.48
Bank	0.065%	2.30%	20				1	0.56
IT	0.069%	1.78%	30					1

Size, value and momentum factors are the returns of "small minus big", "high minus low", and "winner minus loser" in terms of size, book-to-market ratio and three-month return respectively. We use the KOSPI200 index[6] to proxy market portfolio in order to make our results more practical: KOSPI200 related derivatives are popular and their market is one of the most liquid in the world. We approximate daily risk free rate with call rate. Other factors are computed using the returns of 20% and 80% deciles obtained from FnGuide Pro (http://www.fnguide.com). Our trading incorporates transaction cost as follows: 10 bp per unit (brokerage fee + implied costs) whenever buying and 40 bp per unit (brokerage fee + implied costs + transaction tax) whenever selling. In Korea, equity transaction tax (30 bp per unit; stamp tax) is imposed on sellers only. Using this data, we investigate whether simple pair trading strategy works and whether the trading signal can explain heterogeneity or dispersion of stock returns.

Analysis. In line with the mean-reverting AR (1) process, we construct pair trading strategy as: (1) open short position if $\varepsilon_{i,t}$ hits ε_{uo} from below, (2) open long position if $\varepsilon_{i,t}$ hits ε_{do} from above, (3) close if $\varepsilon_{i,t}$ of short position hits ε_{uc}, (4) close if $\varepsilon_{i,t}$ of long position hits ε_{dc}. We set $\varepsilon_{uo} = N^{-1}(.9)\sigma_u$, $\varepsilon_{do} = N^{-1}(.1)\sigma_u$, $\varepsilon_{uc} = N^{-1}(.7)\sigma_u$, and $\varepsilon_{dc} = N^{-1}(.3)\sigma_u$. $N^{-1}(\cdot)$ is inverse cumulative distribution function of standard normal distribution. We chose these points {.1, .3, .7, .9} using a very simple rule – equal distances from center (0.5) – in order to avoid data snooping. In reality, investors usually set asymmetric and dynamic parameters throughout the sample testing. To our satisfaction, with these plain and static parameters, we find very significant results as Table 2 shows.

Table 2. **Performance of long-short portfolio**

$\varepsilon_{i,t}$ is our investment signal for a stock i at time t. In line with the mean-reverting AR(1) process, we rebalance our positions as: (1) open short position if $\varepsilon_{i,t}$ hits ε_{uo} from below, (2) open long position if $\varepsilon_{i,t}$ hits ε_{do} from above, (3) close if $\varepsilon_{i,t}$ of short position hits ε_{dc}, (4) close if $\varepsilon_{i,t}$ of long position hits ε_{dc}. We $\varepsilon_{uo} = N^{-1}(.9)\sigma_u$, $\varepsilon_{do} = N^{-1}(.1)\sigma_u$, $\varepsilon_{uc} = N^{-1}(.7)\sigma_u$, and $\varepsilon_{dc} = N^{-1}(.3)\sigma_u$. $N^{-1}(\cdot)$ is inverse cumulative distribution function of standard normal distribution. In Panel A, Winning Ratio means (# of generating positive profit)/(# of trading), Best performing pair column provides the annualized return of best performing pairs within the corresponding sector, and Worst performing pair is for worst pairs. Last column presents the number of open pairs per day, equal to (numbers stocks with either long or short positions)/2. We use data from January 2005 to January 2011. Estimation period is 60 days. We update the signal daily basis via moving window by 1 day. We deliberately use simplified pair trading to avoid data mining and ensure robustness. First, we do not set the levels for either upper – or lower loss cut to force closing positions in order to avoid data snooping. Second, whenever we open or close trading, we match the number of long and short positions by adding or dropping same number of long and short positions. In Panel B, we regress our pair returns over transaction costs on Fama-French three factors and momentum factor: Returns of Portfolio of Pairs = a + b_1*(KOSPI200 Ret – call rate) + b_2*

[6] http://eng.krx.co.kr/m1/m1_4/m1_4_2/m1_4_2_2/UHPENG01004_02_02_01.html.

SMB Ret + b3* HML Ret + b4*MOM Ret + e. We use KOSPI200 index to proxy market portfolio in order to make our results more practical: KOSPI200 related derivatives are popular and their market is one of the most liquid in the world. Other factors are computed using the returns of 20% and 80% deciles obtained from FnGuide Pro (http://www.fnguide.com). The intercept term ('a') denotes the risk adjusted excess return of our long-short portfolio at each sector. Annualized risk-adjusted excess returns are 35%, 38%, 43%, 18% and 40% in auto, semiconductor, health care, bank and IT sectors respectively. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Panel A. **Summary statistics (annualized; after transaction costs)**

Sector	Average return from pairs	Std. Dev.	Winning Ratio	Best performing pair	Worst performing pair	# of open pairs per day
Auto	42.1%	10.7%	70.6%	86.6%	9.3%	6.52
Semiconductor	48.2%	9.8%	71.5%	75.5%	16.7%	6.98
Health Care	51.4%	12.1%	68.8%	91.6%	9.6%	7.43
Bank	19.0%	5.8%	65.3%	33.2%	4.4%	2.94
IT	50.0%	10.1%	71.8%	90.2%	12.6%	10.73

Panel B. **Testing risk-adjusted returns using Fama-French 3 factors and Momentum factor**

Factors \ Sectors	Auto	Semiconductor	Health Care	Bank	IT
Intercept	0.0014 (0)***	0.0015 (0)***	0.0017 (0)***	0.0007 (0)***	0.0016 (0)***
Market	0.0001 (0.652)	0.0001 (0.347)	0.0002 (0.234)	-0.0001 (0.126)	-0.0001 (0.657)
SMB	-0.0002 (0.345)	0.0002 (0.204)	0.0002 (0.356)	0.0001 (0.548)	-0.0002 (0.440)
HML	-0.0002 (0.557)	0.0001 (0.508)	-0.0001 (0.859)	-0.0001 (0.487)	-0.0002 (0.487)
MOM	-0.0001 (0.590)	0.0001 (0.584)	0.0005 (0.016)*	-0.0002 (0.045)*	0.0001 (0.629)

(Daily returns; P-value in the parenthesis)

In Panel A Winning Ratio means (# of generating positive profit)/(# of trading). Best performing pair column provides the annualized return of best performing pairs within the corresponding sector. Worst performing pair is for the worst pairs. Last column presents the number of open pairs per day, equal to (numbers stocks with either long or short positions)/2. We use data from January 2005 to January 2011. The estimation period is 60 days. We update the signal on the daily basis via moving window by 1 day. We deliberately use crude pair trading to avoid data mining and ensure robustness. First, we do not set the levels for either upper loss cut or lower loss cut to force closing positions. Thus, our position can blow up disastrously if our strategy does not work. Second, whenever we open or close trading, we match the number of long and short positions by adding or dropping same number of long and short positions. This ensures our pair trading balanced.

Panel A clearly suggests that our pair trading strategy generates returns across all sectors large enough to cover transaction costs. Winning ratio is around 70%. Even the worst performing pairs produce profit to make our trading strategy robust and useful to conservative asset managers. Pair trading becomes particularly active in IT sector while rather dormant in bank sector.

Panel B tests whether the profits from the pair trading is the compensation to risk taking or not. We regress our pair returns over transaction costs on Fama-French three factors and momentum factor: (Returns of Portfolio of Pairs) = a + b_1* (KOSPI200 Ret – call rate) + b_2* SMB Ret + b_3* HML Ret + b_4*MOM Ret + e. The intercept term ('a') denotes the risk adjusted excess return of our zero-cost long-short portfolio at each sector. Annualized risk-adjusted excess returns over transaction costs are 35%, 38%, 43%, 18% and 40% in auto, semiconductor, health care, bank and IT sectors respectively. They are statistically significant. It is also interesting to note that the pair trading profits are uncorrelated with standard risk factors. Thus, our results pose challenge to standard multifactor model to explain cross sectional dispersion of stock return.

Table 3 analyzes the relationship between pair trading signals and the dispersion of stock returns. We sort the 100 stocks in the following manner. First, we generate normalized signals (size of trading signal divided by standard deviation of the signal; $\varepsilon_{i,t}/\sigma_u$) for each stock at each rebalancing time. Second, we sort stocks by the signals and construct 4 portfolios with quartiles. Portfolios are labeled as {HH, MH, ML, LL} which contain stocks with highest 25%, next highest 25% and so on respectively upon the normalized signals. We examine 4 holding periods: daily, weekly, biweekly and monthly. For example, biweekly holding strategy sorts stocks and rebalances them every 2 week based on the signal. Our benchmark is equally weighted portfolio of 100 stocks in our universe. All statistics are annualized. The return from the equally-weighted benchmark is by far higher than usual benchmark indices such as KOSPI 200, KOSPI Composite Index and KRX 100. Thus, our results remain robust to other benchmark indices.

Standard deviation of quartile portfolios in the third column remains stable across rebalancing frequency. In comparison, as the holding period gets longer, excess return over benchmark decreases as the fourth column describes. This is not an obvious result because transaction costs increase with trading frequency. Note that the MH and ML portfolios do not show informative trends. Tracking error denotes the annualized standard deviations of excess return over benchmark and transaction costs of quartile portfolios. Thus, information ratio, (Excess return over benchmark)/(Tracking error), shows similar pattern to the excess return: HH > LL and decreases as rebalancing frequency decreases. Interestingly, ML portfolio underperforms LL portfolio, which is an unexpected result to us.

Conclusion. While pair trading has been an important practice for asset managers and traders, prior literature has not investigated whether pair trading opportunities exist in Asian markets. We test a simple pair trading scheme upon statistical arbitrage in the Korean stock market. We start with a standard asset pricing theory to model stock returns with a multifactor model. We select 100 stocks in the most influential 5 sectors in Korea. Then we model their returns using a four-factor model which include sector excess return, value premium, size premium and momentum premium. The model produces idiosyncratic components of each stock, which we model with autoregressive process. As autoregressive process implies mean-reverting stationary process, we can implement pair trading by collecting the stocks most likely converging to their mean. Our simple and robust pair trading method generates annualized risk-adjusted excess returns over transaction costs about 35%, 38%, 43%, 18% and 40% in auto, semiconductor, health care, bank and IT sectors respectively. In addition, the pair trading profits are uncorrelated with standard risk factors.

Our results provide implications to both academic researchers and practical investors. First, our model challenges standard multifactor model in explaining cross – sectional dispersion of stock returns at least in Korean market upon pair trading. We confirmed this result by demonstrating how our trading signal can sort stock returns. Second, investors can implement our idea to enhance the performance of their portfolio. For instance, active fund managers can adjust their asset allocation by changing portfolio weights in line with pair-trading signal. Importantly, this requires asset managers to change their perspectives from stock picking to pair picking.

Many extensions from this paper are possible. We examine only rudimentary pair-trading strategies for robustness and simplicity. More refined strategies may create even larger excess returns. In fact, we have tried more complicated schemes of pair trading. It is not difficult to manufacture excess returns greater than those presented in this paper. Future literature can systematically study such possibilities. In addition, while we carry out our experiment only in the Korean stock market, other financial markets or asset classes can present academic and practical opportunities about pair trading.

Table 3. **Quartile analysis of investment signal**

Rebalancing frequency	25% Quintiles	Std. Dev.	Excess Return over benchmark	Tracking Error	Information Ratio
Daily	HH	29.8%	10.7%	10.1%	1.06
	MH	29.1%	2.6%	8.8%	0.30
	ML	28.5%	-9.3%	8.5%	-1.09
	LL	27.4%	-5.6%	10.7%	-0.52
Weekly	HH	29.2%	7.3%	9.9%	0.74
	MH	28.5%	4.6%	8.9%	0.52
	ML	28.7%	-7.2%	8.5%	-0.85
	LL	28.2%	-6.2%	10.4%	-0.60
Bi-weekly	HH	28.9%	-1.0%	9.2%	-0.11
	MH	28.2%	1.8%	8.7%	0.21
	ML	28.7%	-3.0%	8.6%	-0.35
	LL	28.4%	0.0%	9.9%	0.00
Monthly	HH	27.7%	-2.9%	9.0%	0.32
	MH	28.6%	1.3%	8.6%	0.15
	ML	29.0%	-3.5%	8.6%	-0.41
	LL	28.8%	3.0%	10.0%	0.30

References:

1. *Alexander, C., & Dimitriu, A.* (2005). Indexing and statistical arbitrage. Int. J. Portfolio. Magage. 31(2), 50-63.

2. *Avellaneda, M., & Lee, J.-H.* (2010). Statistical arbitrage in the US – equities market. Int. Quant. Financ. 10(7), 761-782.

3. *Bondarenko, O.* (2003). Statistical arbitrage and securities prices. Int. Rev. Financ. Stud. 16(3), 875 -919.

4. *Fajardo, J., & Lacerda, A.* (2010). Statistical arbitrage with default and collateral. Int. Econ. Lett. 108(1), 81-84.

5. *Fernholz, R., & Maguire, C.* (2007). The statistics of statistical arbitrage. Int. Finan. Anal. J. 63(5), 46-52.

6. *Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G.* (2006). Pairs trading: performance of a relative-value arbitrage rule. Int. Rev. Financ. Stud. 19(3), 797-827.

7. *Hogan, S., Jarrow, R., Teo, M., & Warachka, M.* (2004). Testing market efficiency using statistical arbitrage with applications to momentum and value strategies. Int. J. Financ. Econ. 73(3), 525-565.

8. *Jarrow, R. A., Teo, M., Tse, Y. K., & Warachka, M.* (2005). Statistical arbitrage and market efficiency: enhanced theory, robust tests and further applications. SSRN eLibrary. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=659941

9. *Kaufman, P. J.* (2011). Alpha Trading: Profitable Strategies That Remove Directional Risk. Wiley.

10. *Lehalle, C.-A.* (2009). Rigorous Strategic Trading: Balanced Portfolio and Mean-Reversion. The Journal of Trading, 4(3), 40-46.

11. *Miller, M. H., Muthuswamy, J., & Whaley, R. E.* (1994). Mean reversion of Standard & Poor's 500 index basis changes: arbitrage-induced or statistical illusion? Int. J. Financ. 49(2), 479-513.

12. *Montana, Giovanni, Triantafyllopoulos, Kostas, & Tsagaris,* (2009). Flexible least squares for temporal data mining and statistical arbitrage. Int. Expert. Syst. Appl. 36(2, Part 2), 2819-2830.

13. *Pole, A.* (2007). Statistical arbitrage: algorithmic trading insights and techniques. John Wiley and Sons.

14. *Saks, P., & Maringer, D.* (2008). Genetic programming in statistical arbitrage. Proceedings of the 2008 conference on Applications of evolutionary computing, 73-82.

15. *Stokes, E.* (2004). Market Neutral Investing: Build Consistent Low-Risk Profits by Creating Your Own Hedged Portfolio. Kaplan Publishing.

16. *Triantafyllopoulos, K., & Montana, G.* (2009). Dynamic modeling of mean-reverting spreads for statistical arbitrage. Computational Management Science, 8(1-2), 23-49.

17. *Vidyamurthy, G.* (2004). Pairs Trading: Quantitative Methods and Analysis. Wiley.

18. *Whistler, M.* (2004). Trading Pairs: Capturing Profits and Hedging Risk with Statistical Arbitrage Strategies. John Wiley and Son.

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