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Original Paper

European Equity Pairs Trading: The Effect of Data Frequency on Risk and Return

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Abstract

This article examines an equity pairs trading strategy using daily, weekly and monthly European share price data over the period 1998 – 2007. The authors show that when stocks are matched into pairs with minimum distance between normalised historical prices, a simple trading rule based on volatility between these prices yields annualised raw returns of up to 15% for the weekly data frequency. Bootstrap results suggest returns from the strategy are attributable to skill rather than luck, while insignificant beta coefficients provide evidence that this is a market neutral strategy. Resistance of the strategy's returns to reversal factors suggest pairs trading is fundamentally different to previously documented reversal strategies based on concepts such as mean reversion.

Keywords

pairs trading, market neutrality, co-integration

1. Introduction

Investors, be they individuals or institutions, have long been interested in developing and implementing quantitative techniques to make speculative profits in financial markets. One relatively modern and popular short-term speculation strategy, known as pairs trading, was developed on Wall Street in the mid-1980s as a means of exploiting potential arbitrage opportunities in the stock market.

The concept of pairs trading is relatively transparent. It involves finding two assets whose prices have moved together historically. When the spread between these two assets widens a position is opened by shorting the asset whose price has increased and/or going long the asset whose price has fallen. If the prices return to the historical trend then the position is closed by covering the short position and selling the long asset and so a profit is made.

This article looks at the profitability of an equity pairs trading strategy in a European context prior to the financial crisis which ravaged global markets in late 2007/early 2008. It documents several interesting characteristics of such a strategy. First, it tests the effect of price data frequency (daily, weekly and monthly) on the profitability of the strategy's positions. It finds that pairs trading, with weekly frequency data, generated the greatest number of positive raw returns, as well as the largest, which persisted after transaction costs. Comparing these returns to the risk-free rate resulted in comprehensive excess returns (before and after transaction costs). Surprisingly, the performance of the strategy with daily data was not as consistent. While the strategy generated positive raw and excess returns before transaction costs it was not able to provide any positive excess returns after transaction costs.

Second, it looks at the risk characteristics of the strategy, in particular, the concept of market neutrality. The study finds that the strategy enhances portfolio alpha. When regressed on a composite index of the CAC40 and Xetra DAX, for daily and weekly frequencies, the returns generated positive and significant alphas, meaning that the strategy has a positive abnormal return after filtering for market factors. It finds also, that the beta coefficients for the strategy are small and close to zero with none significant at daily or weekly frequencies. This result supports the concept of pairs trading as a market neutral strategy.

Third, it looks at the skillfulness of the strategy by comparing the returns to randomly simulated trades. For daily and weekly data frequencies, the returns due to pairs trading are far superior to those which could be attributed to luck, with the strategy beating between 93% and 100% of random portfolios. While the very best returns attributable to random trading do, in a very few cases, beat those of the pairs strategy, they occur in such an insignificant percentage of the simulations that they represent nothing more than chance. There are also indications of positive performance of the monthly frequency data returns over the random returns; however, they are not as significant as the higher frequency data.

2. Methodology

2.1 Dataset

The concept of pairs trading involves identifying two stocks whose prices have moved together historically. This idea has strong parallels with the econometric concept of co-integration and allows a pairs trading strategy to be justified within an equilibrium asset pricing framework, similar to that proposed by Bossaerts and Green (1989) who, developed and tested a general equilibrium model based on the concept of co-integrated prices. They found that individual securities change through time in predictable ways similar to Engle and Granger (1987) and Bossaerts (1988) who found evidence of co-integration for the US stock market.

The concept of co-integration postulates that two series, (e.g. stock prices), may move randomly through time but while the movement of the individual series may be random; there is some linear or predictable relationship between them. This idea fits well with the premise of pairs trading.

This concept is applied to a dataset of the most liquid stocks from the French and German stock markets. Taking 10 years of daily, weekly and monthly price data for these markets, between 1998 and 2007 inclusive, stocks with consecutive observations with no trade (consecutive days for daily, weeks for weekly and months for monthly frequencies) are first screened out. This screening is done to identify relatively liquid stocks and to facilitate pairs formation. This process follows the methods of previous studies, namely Gatev (2006), who observed that stale or static price data may lead to biases in the formation of pairs with no movement in prices being misinterpreted as co-movement.

Table 1. Dataset According to Time Series Frequency

Frequency	Number of Stocks			Number of Observations for Each Stock	Total Number of Observations
	French	German	Total		
Daily	44	30	74	2158	159692
Weekly	86	68	154	525	80850
Monthly	183	72	255	120	30600

Looking at Table 1 it is evident that the majority of liquidity problems occurred with the daily prices where only 74 stocks were selected. For weekly and monthly stock prices such liquidity problems were not as severe. This is to be expected, however, and still allowed for sufficient observations from which significant results could be returned.*2.2 Pairs Trading*

The first step in the formation of pairs is to select the length of the moving formation (training) period over which liquid stocks are paired.

This study began with a twelve month formation period but an initial inspection of pairs formed on this basis were found to be weak, unravelling significantly in the following period. This study, therefore, uses a twenty four month formation period.

The next step in the process is to transform all stock prices to a common unit which makes it easier to identify co-movement in stock prices. This common unit is normalised price.

$$P_{it}^{*} = \frac{P_{it} - E\left(P_{it}\right)}{\sigma_i}$$

Where:

P^{*}_{it} = the normalised price of stock i at time t

P_{it} = the price of stock i at time t

$E(P_{it})$ = the expected price of stock i at time t i.e. its mean

σ_i = the standard deviation of stock i

The rationale behind using a common measure, such as normalised price, is that it allows the formation of pairs using a standard econometric procedure known as minimum squared distance (similar to the concept of ordinary least squares or OLS).

Previous work by Gatev (2006) and Perlin (2009) use a minimum squared distance procedure, normalising all stock prices and then pairing stocks which have the minimum squared distance between their normalised price series. It is at this point that the use of a common unit i.e. normalised price, becomes important. Using original prices with a minimum squared distance rule may prove problematic when trying to identify pairs. While two stocks may appear to move together in original price space they may still have a high squared distance between them.

Once the stock prices have been transformed to a common measure the next step is to choose, for each stock, a pair which has the minimum squared distance between the normalised price series of each stock. The normalised price for the pair of stock *i* can now be termed p^*_{it}. After the pair of each stock is identified, a trading system is created.

The first step in the trading of the pairs created in the formation period is to select the length of the moving trading period over which pairs are traded. This study uses a trading period of six months, which a common timeframe in previous literature.

Once all liquid stocks have been paired up in the formation period a trading rule is created whereby a position is opened every time the absolute distance between P^*_{it} and p^*_{it} is higher than a predetermined threshold value (measured by normalised price) which we call *d*. The value of this threshold value, *d*, is subjective and represents a rule for the creation of a trading signal. Intuitively, the value of *d* should not be very high, otherwise no trades will take place nor should it be too low as this will result in too many trades and hence high transaction costs.

Because the selection of *d* is entirely subjective and, because intuitively we know that it should not be too high or too low, a range of normalised price based threshold values are tested. This gives the study flexibility by not imposing restrictive assumptions and also allows the testing of the impact of different threshold values on the strategy's performance.

A position in a pair is opened when P^*_{it} and p^*_{it} diverge by more than *d* and close when the prices next converge. If the prices do not converge before the end of the trading period, gains/losses are calculated at the end of the last trading day of that trading period. Similarly, if a stock in a pair is delisted or becomes inactive during the period then the position is closed using the last available price.

3. Results

3.1 Returns Analysis

Payoffs to the pairs strategy are calculated as a set of positive cash flows (positions which are opened when the prices diverge and are then closed once the prices converge) that are randomly distributed throughout the trading period, and a set of cash flows at the end of the period which can be positive or negative (positions which are opened when the prices diverge but do not converge and so remain open at the end of the period). Raw returns are computed as the sum of payoffs during the trading period.

While the strategy may have positive and significant raw returns it is also necessary to compare them against a suitable benchmark in order to make robust evaluations. In this case the raw returns from the pairs trading strategy, for each frequency, are compared to the risk-free rate. The interest rate, on French and German Government Bonds, is taken here as the risk free rate.

Looking at the strategy's raw return, with and without transaction costs, one can see that pairs trading is profitable, particularly with weekly and daily frequency data. Table 2 shows that for the weekly frequency data, annual returns range from 7.35% to 14.84% (4.77% to 13.42% with transaction costs) with annual returns of between 3.97% and 10.21% (-5.77% and 5.08% with transaction costs) for daily frequency data. The strategy is less profitable, however, using monthly frequency data, with much more modest returns of between -1.23% and 3.88% (-1.64% and 2.73% with transaction costs).

Table 2. Pairs Trading Raw Returns

Threshold	Total Raw Return (No Transaction Costs)			Total Raw Return (With Transaction Costs)		
Value	Daily	Weekly	Monthly	Daily	Weekly	Monthly
1.5	8.72%	9.11%	3.88%	-5.77%	4.77%	2.51%
1.6	10.21%	10.79%	3.22%	-2.02%	7.30%	1.83%
1.7	9.96%	12.28%	1.65%	-0.47%	9.37%	0.16%
1.8	9.28%	12.75%	2.34%	-0.49%	10.18%	1.09%
1.9	9.19%	13.35%	1.05%	1.36%	11.03%	-0.08%
2	8.31%	13.69%	1.01%	1.02%	11.56%	0.19%
2.1	8.66%	14.84%	-1.08%	3.02%	13.11%	-1.64%
2.2	9.08%	14.33%	-0.88%	4.21%	12.71%	-1.35%
2.3	7.06%	14.84%	-1.23%	2.12%	13.42%	-1.59%
2.4	6.69%	14.18%	0.34%	2.28%	12.96%	0.03%
2.5	7.15%	13.36%	1.74%	3.69%	12.22%	1.51%
2.6	7.99%	11.97%	2.85%	5.08%	10.93%	2.73%
2.7	7.00%	9.66%	1.00%	4.48%	8.50%	0.95%
2.8	5.96%	8.27%	1.00%	3.55%	7.28%	0.95%
2.9	6.61%	7.80%	1.00%	4.77%	6.87%	0.95%
3	3.97%	7.35%	-0.01%	2.26%	6.51%	-0.03%

Analysis of the excess returns of the strategy, in Table 3, without transaction costs, show that the pairs trading strategy was in excess of the risk-free rate over the period for only the daily and weekly frequency data. However, only the weekly data had positive excess returns when transaction costs were taken into consideration. Even after transaction costs the weekly frequency data showed average annualised excess returns of 5.54%, with annualised excess returns of between 7.18% and 9.04% for threshold values (measured by normalised prices) of between 2 and 2.5 inclusive.

Table 3. Pairs Trading Excess Returns

Threshold Value	Total Raw Return (No Transaction Costs)			Total Raw Return (With Transaction Costs)		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
1.5	4.34%	4.73%	-0.50%	-10.15%	0.39%	-1.87%
1.6	5.83%	6.41%	-1.16%	-6.40%	2.92%	-2.55%
1.7	5.58%	7.90%	-2.73%	-4.85%	4.99%	-4.22%
1.8	4.90%	8.37%	-2.04%	-4.87%	5.80%	-3.29%
1.9	4.81%	8.97%	-3.33%	-3.02%	6.65%	-4.46%
2	3.93%	9.31%	-3.37%	-3.36%	7.18%	-4.19%
2.1	4.28%	10.46%	-5.46%	-1.36%	8.73%	-6.02%
2.2	4.70%	9.95%	-5.26%	-0.17%	8.33%	-5.73%
2.3	2.68%	10.46%	-5.61%	-2.26%	9.04%	-5.97%
2.4	2.31%	9.80%	-4.04%	-2.10%	8.58%	-4.35%
2.5	2.77%	8.98%	-2.64%	-0.69%	7.84%	-2.87%
2.6	3.61%	7.59%	-1.53%	0.70%	6.55%	-1.65%
2.7	2.62%	5.28%	-3.38%	0.10%	4.12%	-3.43%
2.8	1.58%	3.89%	-3.38%	-0.83%	2.90%	-3.43%
2.9	2.23%	3.42%	-3.38%	0.39%	2.49%	-3.43%
3	-0.41%	2.97%	-4.39%	-2.12%	2.13%	-4.41%

Verifying the relationship between the threshold value and the number of trades in each period, it is evident that they are negatively correlated. This is because the threshold value represents an abnormal price divergence. As this value increases, the occurrences of abnormal divergences decreases and so less transactions are made.

Looking at the raw returns in Table 2, one can see that pairs trading remains profitable in most cases after including transaction costs. The strategy, using weekly frequency data, remains the most profitable after transaction costs with returns dropping from between 7.35% and 14.84% before to between 4.77% and 13.11% after.

As expected transaction costs have the greatest effect on returns at the lower threshold values of between 1.5 and 2. Also, as expected the returns to pairs trading, using higher frequency data, are more sensitive to transaction costs than those for less frequent trading. This can be seen clearly between the daily and monthly frequencies. The difference between the highest return without transaction costs and with transaction costs for daily is 5.13% compared to only 1.15% for monthly while the difference between the worst returns is 9.74% and 0.56% respectively. Weekly frequency data returns, without and with transaction costs, differ by 1.42% for the best return and 2.58% for the worst.

However, looking at the excess returns in Table 3 one can see that only the weekly frequency remains profitable after transaction costs. Before transaction costs the average annualised weekly excess returns are on average 7.4%, dropping to 5.5% after transaction costs. Both the daily and monthly frequencies show significantly negative excess returns after transaction costs.

Looking at the long and short positions in isolation in Table 4, we can see that, at both the weekly and monthly frequencies the long positions are more profitable than the short, particularly for monthly where the difference is on average 5.94%. However, the returns attributable to the long and short positions for the daily frequency differ significantly from those for weekly and monthly. For daily the long positions outperform the short for threshold values between 1.5 and 1.8 inclusive while the short positions then outperform the long for threshold values from 1.9 to 3.

Table 4. Pairs Trading Long & Short Positions

	Total Raw Return (No Transaction Costs)					
Threshold	**Daily**		**Weekly**		**Monthly**	
Value	**Long**	**Short**	**Long**	**Short**	**Long**	**Short**
1.5	11.81%	4.49%	9.82%	8.40%	7.97%	-2.17%
1.6	12.62%	7.15%	11.40%	9.96%	7.58%	-2.77%
1.7	11.35%	8.30%	13.29%	11.18%	7.47%	-5.25%
1.8	9.73%	8.83%	14.11%	11.18%	8.30%	-5.34%
1.9	8.72%	9.50%	15.13%	10.92%	7.04%	-5.78%
2	7.87%	8.67%	15.08%	11.77%	7.23%	-6.05%
2.1	7.41%	9.75%	16.19%	13.22%	2.53%	-4.21%
2.2	8.97%	9.36%	15.57%	12.97%	1.50%	-2.99%
2.3	5.28%	8.65%	16.53%	12.95%	1.19%	-3.32%
2.4	6.91%	6.40%	15.57%	12.65%	2.18%	-1.64%
2.5	6.03%	7.92%	14.98%	11.47%	1.97%	1.51%
2.6	5.09%	9.98%	13.98%	9.38%	3.85%	1.77%
2.7	2.30%	10.09%	11.36%	7.58%	0.90%	1.10%
2.8	-0.42%	9.79%	10.47%	5.59%	0.90%	1.10%
2.9	1.68%	9.86%	10.96%	3.45%	0.90%	1.10%
3	2.06%	5.37%	10.42%	3.43%	0.10%	-0.13%

While one may be able to adapt the strategy to a long only one in the case of monthly or long/short only in the case of weekly to make it more profitable the result from the daily frequency raises questions. Why do the long positions outperform the short up to a certain point and then swap over to being outperformed? This could be to do with investor psychology with the market not willing to buy stocks that have fallen by a certain amount on a day or profit taking on stocks that have gone up by a certain amount. It may also be due to the fact that momentum does not have to be symmetrical.

Table 5 shows the Sharpe Ratios associated with the returns of the strategy at the different frequencies.

Table 5. Pairs Trading Sharpe Ratios

Threshold	**Sharpe Ratio (No Transaction Costs)**			**Sharpe Ratio (With Transaction Costs)**		
Value	**Daily**	**Weekly**	**Monthly**	**Daily**	**Weekly**	**Monthly**
1.5	4.75	3.36	-0.12	-11.12	0.28	-0.44
1.6	5.67	4.38	-0.26	-6.22	2	-0.57
1.7	5.41	4.53	-0.61	-4.7	2.86	-0.94
1.8	4.73	4.47	-0.44	-4.7	3.09	-0.72
1.9	4.54	4.43	-0.72	-2.85	3.29	-0.97
2	3.62	4.61	-0.82	-3.1	3.56	-1.02
2.1	4.01	4.5	-1.62	-1.27	3.76	-1.78
2.2	4.66	4.19	-1.72	-0.17	3.51	-1.88
2.3	2.61	3.87	-2.02	-2.21	3.35	-2.15
2.4	2.38	3.78	-1.61	-2.17	3.31	-1.73
2.5	2.81	3.47	-1.06	-0.7	3.03	-1.15
2.6	3.89	3	-0.68	0.75	2.59	-0.73
2.7	2.91	2.17	-4.17	0.11	1.7	-4.23
2.8	1.73	1.81	-4.17	-0.91	1.35	-4.23
2.9	2.54	1.65	-4.17	0.44	1.2	-4.23
3	-0.52	1.48	-315.07	-2.7	1.06	-316.5

Without transaction costs, the pairs trading strategy had positive risk-adjusted performance over the period for the daily and weekly frequency data only. However, only the weekly frequency had positive Sharpe Ratios when transaction costs were taken into consideration. Even after transaction costs the weekly frequency showed an average Sharpe Ratio of 2.5, with ratios of between 3.31 and 3.76 for threshold values (measured by normalised prices) of between 2 and 2.4 inclusive. This highlights the fact that the strategy, using weekly data, provides the best risk-adjusted performance of the three frequencies, particularly when transaction costs are taken into consideration.

3.2 Risk Analysis

Table 6 presents analysis of the risk associated with the pairs trading strategy at the different researched frequencies over a range of threshold values. The Alpha and Beta coefficients are obtained by regressing the portfolio returns on a weighted composite index of the CAC40 and Xetra DAX.

Table 6. Pairs Trading Jensen's Alpha and Beta

Panel A : Pairs Trading - Daily Frequency				
Threshold Value	**Alpha**	**Prob**	**Beta**	**Prob**
1.5	0.00183	0.00000***	0.00051	0.48362
1.6	0.00294	0.00000***	0.06583	0.75153
1.7	0.00361	0.00000***	0.07480	0.52444
1.8	0.00345	0.00000***	0.08018	0.33269
1.9	0.00330	0.00000***	0.06665	0.47801
2	0.00300	0.00000***	0.07046	0.33789
2.1	0.00278	0.00000***	0.07631	0.62070
2.2	0.00271	0.00000***	0.07058	0.52903
2.3	0.00252	0.00000***	0.06699	0.55211
2.4	0.00220	0.00000***	0.07443	0.42247
2.5	0.00189	0.00000***	0.07110	0.58256
2.6	0.00187	0.00000***	0.05124	0.55567
2.7	0.00174	0.00000***	0.05409	0.48402
2.8	0.00157	0.00000***	0.04303	0.25428
2.9	0.00146	0.00000***	0.04768	0.13313
3	0.00130	0.00000***	0.02779	0.32110
Panel B : Pairs Trading - Weekly Frequency				
Threshold Value	**Alpha**	**Prob**	**Beta**	**Prob**
1.5	0.00574	0.00000***	-0.00204	0.53350
1.6	0.00625	0.00000***	-0.02395	0.82903
1.7	0.00727	0.00000***	-0.00596	0.57852
1.8	0.00725	0.00000***	0.01098	0.36700
1.9	0.00734	0.00000***	-0.00239	0.52730
2	0.00728	0.00000***	0.01129	0.37273
2.1	0.00811	0.00000***	-0.01926	0.68471
2.2	0.00762	0.00000***	-0.00864	0.58358
2.3	0.00795	0.00000***	-0.01289	0.60904
2.4	0.00743	0.00000***	0.00381	0.46604
2.5	0.00670	0.00000***	-0.01630	0.64264
2.6	0.00555	0.00000***	-0.01251	0.61298
2.7	0.00414	0.00028***	-0.00356	0.53393
2.8	0.00337	0.00074***	0.02150	0.28051
2.9	0.00304	0.00142***	0.03745	0.14675
3	0.00286	0.00187***	0.01291	0.35421
Panel C : Pairs Trading - Monthly Frequency				
Threshold Value	**Alpha**	**Prob**	**Beta**	**Prob**
1.5	0.00550	0.00000***	-0.01665	0.83527
1.6	0.00461	0.00000***	-0.02932	0.94729
1.7	0.00272	0.00263***	-0.03880	0.98413
1.8	0.00353	0.00020***	-0.09333	1.00000

1.9	0.00196	0.02539**	-0.05756	0.99901
2	0.00105	0.12162	0.00194	0.45352
2.1	-0.00129	0.96045	0.04546	0.00044***
2.2	-0.00110	0.95322	0.07972	0.00000***
2.3	-0.00153	0.99482	0.08750	0.00000***
2.4	0.00022	0.34555	0.06524	0.00000***
2.5	0.00183	0.00031***	0.06859	0.00000***
2.6	0.00337	0.00000***	0.04250	0.00000***
2.7	0.00109	0.00000***	0.00438	0.08837*
2.8	0.00109	0.00000***	0.00438	0.08837*
2.9	0.00109	0.00000***	0.00438	0.08837*
3	0.00001	0.00000***	0.00028	0.00000***

*** Significant at 1% level

** Significant at 5% level

* Significant at 10% level

Table 6 looks firstly at Jensen's Alpha, a risk-adjusted performance measure that represents the average return on a portfolio over and above that predicted by the capital asset pricing model, which should be positive and statistically significant if the strategy has performance which cannot be explained by the market. We can see from Panels A and B that the daily and weekly frequency returns have positive and significant alphas at all threshold values meaning that the pairs trading strategy has a positive abnormal return after filtering for market factors.

The second coefficient in Table 6 is the pairs trading strategy's Beta. This is a measure of the volatility, or systematic risk, of the portfolio in comparison to the market as a whole. The higher the beta of an asset the more correlated with the market it is i.e. the greater its market risk and the more exposed it is to changes in the market it is. All the beta coefficients are small and close to zero with Panels A and B showing none of them to be significant at daily or weekly frequencies. This result supports the concept of pairs trading as a market neutral strategy, meaning its returns are not dependent on market movements. These findings are not unexpected, however. In the pairs trading framework, the execution of a long and a short position in a stock at the same time naturally creates a hedge against market movements.

3.3 Skill vs. Luck

The use of bootstrapping has become standard in recent research on the performance of investment strategies and the skill of investment managers. Bootstrapping is a method which allows the comparison of the actual returns from a strategy or investment product against a series of randomly generated returns. Basically it tests whether the returns attributable to the strategy are due to skill or whether they may be just as easily arrived at due to random luck. The idea is to synthetically create random market entries, saving the performance for each simulation and then testing these against the performance of the actual values. If the measures of performance attributable to the strategy are not significantly different from those generated by random signals (chance) then one may conclude that the strategy's returns can just as easily be accredited to luck as to skill. The results from the bootstrap simulations are shown in Table 7.

Table 7. Pairs Trading Returns versus Bootstrap Simulations

Panel A - Daily Frequency								
Threshold Value	**% Days in Market**	**No. Trades**	**Raw Ret No TC**	**% Random Portfolios Beaten**	**Top Random Return**	**Raw Ret TC**	**% Random Portfolios Beaten**	**Top Random Return**
1.5	76.38%	1030	8.72%	100%	6.40%	-5.77%	100%	-6.40%
1.6	75.08%	932	10.21%	100%	8.02%	-2.02%	100%	-6.20%
1.7	72.97%	816	9.96%	100%	7.90%	-0.47%	100%	-4.00%
1.8	69.56%	740	9.28%	100%	8.00%	-0.49%	100%	-3.70%
1.9	64.88%	632	9.19%	100%	6.90%	1.36%	100%	-3.50%
2	59.74%	558	8.31%	99.80%	10.01%	1.02%	100%	-2.00%
2.1	54.22%	474	8.66%	100%	7.60%	3.02%	100%	-1.20%
2.2	49.16%	437	9.08%	100%	8.90%	4.21%	100%	2.50%
2.3	44.36%	373	7.06%	97.35%	10.20%	2.12%	99.75%	4.95%
2.4	39.65%	329	6.69%	97.40%	10.50%	2.28%	99.90%	4.00%
2.5	34.05%	275	7.15%	98.75%	8.90%	3.69%	99.00%	3.92%
2.6	31.17%	258	7.99%	99.65%	10.00%	5.08%	99.90%	5.00%
2.7	27.45%	209	7.00%	99.05%	9.00%	4.48%	99.95%	5.10%
2.8	23.47%	184	5.96%	97.60%	10.02%	3.55%	100.00%	2.40%
2.9	20.02%	151	6.61%	99.45%	9.80%	4.77%	100.00%	2.40%
3	16.83%	113	3.97%	93.45%	8.40%	2.26%	99.85%	3.80%
Panel B - Weekly Frequency								
Threshold Value	**% Weeks in Market**	**No. Trades**	**Raw Ret No TC**	**% Random Portfolios Beaten**	**Top Random Return**	**Raw Ret TC**	**% Random Portfolios Beaten**	**Top Random Return**
1.5	79.69%	399	9.11%	96.80%	15.70%	4.77%	93.20%	13.31%
1.6	78.54%	382	10.79%	98.40%	15.53%	7.30%	97.90%	15.08%
1.7	78.16%	367	12.28%	99.70%	14.26%	9.37%	99.60%	12.33%
1.8	76.63%	342	12.75%	99.70%	15.31%	10.18%	99.40%	13.67%
1.9	75.10%	327	13.35%	100%	13.06%	11.03%	99.40%	11.91%
2	72.03%	311	13.69%	100%	10.37%	11.56%	100%	10.93%
2.1	67.43%	281	14.84%	100%	13.91%	13.11%	100%	11.15%
2.2	62.45%	253	14.33%	100%	13.66%	12.71%	100%	9.91%
2.3	57.66%	234	14.84%	100%	12.21%	13.42%	100%	10.63%
2.4	50.57%	192	14.18%	100%	12.48%	12.96%	99.90%	13.93%
2.5	45.02%	169	13.36%	100%	11.54%	12.22%	100%	11.78%
2.6	38.31%	139	11.97%	100%	8.96%	10.93%	99.90%	11.08%
2.7	34.29%	126	9.66%	99.90%	9.84%	8.50%	100%	7.56%
2.8	28.35%	101	8.27%	99.90%	11.90%	7.28%	99.90%	8.94%

2.9	25.10%	88	7.80%	99.70%	9.09%	6.87%	99.80%	8.07%
3	22.22%	77	7.35%	99.80%	8.57%	6.51%	99.90%	7.17%
Panel C - Monthly Frequency								
Threshold Value	**% Months in Market**	**No. Trades**	**Raw Ret No TC**	**% Random Portfolios Beaten**	**Top Random Return**	**Raw Ret TC**	**% Random Portfolios Beaten**	**Top Random Return**
1.5	77.50%	91	3.88%	80.90%	21.19%	2.51%	75.40%	15.34%
1.6	74.17%	87	3.22%	76.60%	22.13%	1.83%	71.60%	20.18%
1.7	70.00%	81	1.65%	66.50%	26.49%	0.16%	57.20%	19.90%
1.8	62.50%	73	2.34%	74.80%	17.65%	1.09%	65.10%	21.97%
1.9	50.00%	59	1.05%	60.70%	15.60%	-0.08%	53.10%	10.74%
2	36.67%	43	1.01%	62.90%	10.93%	0.19%	56.20%	17.79%
2.1	26.67%	32	-1.08%	34.80%	16.27%	-1.64%	27.50%	12.60%
2.2	21.67%	26	-0.88%	34.50%	10.33%	-1.35%	31.20%	11.79%
2.3	16.67%	20	-1.23%	27.50%	11.69%	-1.59%	24.20%	11.28%
2.4	13.33%	16	0.34%	59.10%	7.02%	0.03%	56.20%	7.48%
2.5	10.83%	13	1.74%	84.00%	8.05%	1.51%	82.00%	8.67%
2.6	6.67%	8	2.85%	97.30%	7.37%	2.73%	96.90%	7.86%
2.7	2.50%	3	1.00%	88.10%	3.91%	0.95%	86.40%	3.32%
2.8	2.50%	3	1.00%	88.10%	3.91%	0.95%	86.40%	3.32%
2.9	2.50%	3	1.00%	88.10%	3.91%	0.95%	86.40%	3.32%
3	0.83%	1	-0.01%	50.00%	3.16%	-0.03%	50.40%	3.12%

For daily and weekly frequencies the returns due to pairs trading are far superior to those which could be attributed to luck with the strategy beating between 93% and 100% of the random portfolios for each threshold value. While the very best returns attributable to random trading do in a very few cases beat those of the pairs strategy, they occur in such an insignificant percentage of the simulations that they represent nothing more than chance.

There are also indications of positive performance of the monthly frequency returns over the bootstrap returns; however, they are not as significant as the higher frequencies (beating between 24% and 80% of the random portfolios). Also the fact that this frequency had much fewer trades means that these results cannot be conclusively used in assessing pairs trading performance.

4. Discussion

Overall the best returns for the strategy are attributable to the weekly frequency data. Pairs trading with weekly frequency data generated the greatest number of positive raw returns as well as the largest at all thresholds which persisted after transaction costs. Comparing these returns to the risk-free rate and random portfolios resulted in comprehensive excess returns (before and after transaction costs) and positive Sharpe Ratios while also showing that the returns are much more skill than luck.

Surprisingly, the performance of the strategy with daily data was not as consistent. While the strategy generated positive raw and excess returns before transaction costs it was not able to provide any positive excess returns or Sharpe Ratios after transaction costs. These findings contradict those of Gatev (2006) and Perlin (2009) who found daily frequency pairs trading to be profitable. It may be the case that high frequency trading is more sensitive to transaction costs in the European market than the US or Brazil and that for this market, pairs trading using weekly frequency data, is optimal.

The performance of the strategy with monthly data was not consistent for different threshold values and while positive raw returns were found the comparison with simulated portfolios seems to suggest most of the returns at this frequency may be just a case of chance rather than skill.

Finally, this article looks at an equity pairs trading strategy prior to the financial crisis which began in late 2007/early 2008, the effects or which still persist today, particularly in the European case. Given the role of market neutrality in pairs trading, it would be interesting for further study to look at this unique time period of market volatility and explore if indeed pairs trading can remain profitable and market neutral in such an environment.

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