The Stability of Moving Average Technical Trading Rules on the Dow Jones Index

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Abstract

This paper analyzes the behavior of moving average technical trading rules applied to over 100 years of the Dow Jones Industrial Index. It is found that the differences between conditional means during buy and sell periods has changed dramatically over the previous 10 years relative to the previous 90 years of data, but differences in conditional variances have not changed much over the entire sample. Further robustness checks indicate that similar results could be obtained with simple momentum based strategies. The analysis is performed on the actual Dow series, but these techniques could be useful in derivative markets where better estimates of conditional means and variances would be useful information.

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1 Introduction

The ability of simple rules to predict asset price movements, or technical analysis, has been a controversial subject for many years. While the academic community has generally held technical analysts in disdain, its recent fascination with predictability has reopened many of the old cases against technical analysis. Rather than simply ignoring the rules used by technicians academics have been carefully scrutinizing them.[1] The evidence still seems somewhat inconclusive on the usefulness of these rules, but this is in contrast to the earlier results that suggested that anyone following these was less than rationally motivated.

The modern literature has moved forward in bringing to bear more rigorous tests and econometric methodology. The introduction of the bootstrap allows testing of various complex null hypothesis for which analytic approaches would be impossible. It also offers a possible method to adjust for the biases induced by data snooping. To the econometrician, technical trading rules can be viewed as simply another set of moment conditions that can either be used in specification testing, or in estimation.[2] They therefore play a dual role as an interesting behavior which might have some practical value, and as a data description that economic theorists should be aware of.

This paper reexamines the Dow Jones Industrials with respect to simple moving average rules. Using the Dow Jones Industrials, Brock et al. (1992) showed that moving average technical trading rules had some predictive abilities in both conditional means and variances. Further, they showed that these results were relatively stable over their 90 year sample period. Recently Sullivan, Timmerman & White (1999) demonstrated that while it appears unlikely that these rules were "snooped" from the earlier sample, their forecasting performance over recent years has disappeared. This important result raises many serious questions about trading rules, and the stationarity of financial time series. This paper further explores the performance of these rules and compares the previous 10 years to the rest of the century. When analyzed in light of moving average trading rules, some very interesting similarities and differences appear.

This paper corroborates and extends the results in Sullivan et al. (1999). First, analysis is performed on conditional variances as well as conditional means. Secondly, some further robustness checks are performed, along with some comparisons with other rules. Specifically, a simpler momentum based dynamic strategy appears to be very similar to the moving average rules.

The tests implemented in this paper are only concerned with the cash market. However, there is a direct

[1]The earliest tests critiquing technical rules were in Fama & Blume (1966). See Brock, Lakonishok & LeBaron (1992) for an extensive summary of the literature on technical trading. For a recent example of some of the latest evidence, see Acar & Satchell (1998).

[2]For an example of the latter see LeBaron (1992).

impact of these technologies in various derivatives markets. First, mean predictability can impact options pricing as in Lo & Wang (1995). Also, it is obvious that a useful predictor of second moments might provide better dynamic trading strategies in options markets as in Engle & Mustafa (1992), or as a value at risk estimation tool.

The first section describes the century long series of daily Dow data. The second section looks at various measures of conditional means during the pre and post 1986 periods. The third section performs similar tests on conditional variances. The fourth section provides some robustness checks on the technical trading rules, and shows that it is possible that even simpler rules might generate similar results. The final section concludes and returns to the questions about data snooping, and data stationarity in light of this new evidence.

2 Data

The data used will be the daily Dow Jones Industrials from January 1897 through February, 1999. This series includes the series used in Brock et al. (1992) (henceforth BLL) as a subset, but adds another 10 years after their stopping point in 1986. This extra 10 years of data is started in 1988 to avoid the run up and crash of 1987 which would have a dramatic impact on such a short sample. The full series includes a total of 24645 days. The series used do not include dividends, so some care should be taken in using these series in evaluating long range performance. Since this paper concentrates on the behavior of conditional means and variances alone, the addition of the aggregate dividend process would probably not affect the results much.

Table 1 shows some summary statistics for the daily returns for several of the subsamples that will be considered. Returns are calculated as log differences,

$$r_t = \log(P_t) - \log(P_{t-1}), \tag{1}$$

for all cases considered in this paper. The table shows very little new information for those familiar with relatively high frequency asset price series. There is a large amount of excess kurtosis in all the subsamples which is a common feature. One interesting characteristic that is a little unusual is the large daily returns that have occurred over the last decade. While it is well known that the Dow has been rising steadily, it is surprising that the daily return is nearly 3 times the average over the century.

Table 1: *Summary Statistics*

	1897-1999(Feb)	1897-1986	1988-1999(Feb)
Mean (%)	0.020	0.015	0.056
Var*100	0.011	0.011	0.008
Skewness	-0.622	-0.110	-0.572
Kurtosis	26.4	15.7	9.45

3 Conditional Means

This paper uses commonly applied moving average technical trading rules for most tests. These compare the price with a moving average of past prices,

$$m_t = \frac{1}{N} \sum_{i=0}^{N-1} P_{t-i}. \tag{2}$$

There are many possible combinations of moving averages that are used in practice, but this paper will concentrate on a very simple implementation. A day is considered to have a buy signal when $P_t \geq m_t$, and a sell signal when $P_t < m_t$.[3] The rule is then applied to the return from t to $t+1$. Conditional means and variances will be estimated over this period, and classified as either buy or sell depending on the time t signal. One of the most consistent performing rules historically is one that uses $N = 150$ days. This rule alone will be used. Earlier papers, Brock et al. (1992) and LeBaron (1998) have already shown that it works well over many different time periods. Further, LeBaron (1998) shows that a wide range of rules from $N = 50$ to $N = 200$ generate similar results.

Table 2 presents estimates of the conditional mean return during buy and sell periods indicated by the 150 day moving average rule. The first column, labeled Buy-Sell, reports the difference between the conditional mean from the buy and sell periods. The second column, labeled Buy-All, reports the difference between the Buy period returns and the unconditional mean return over the appropriate sample. Sell-All reports a similar estimate for the sell periods. The numbers in parenthesis are a simple t-statistic which under the null hypothesis that the means are equal would be distributed $N(0,1)$.[4] The numbers in brackets are simulated p-values from 1000 bootstrap simulations of a random walk. This method generates new return

[3] This corresponds to one of the set of rules used in Brock et al. (1992).

[4] The t-stats are formed as

$$z = \frac{\mu_b - \mu_s}{\sqrt{\sigma_b^2/N_b + \sigma_s^2/N_s}}.$$

Similar numbers are used for the Buy-All, Sell-All cases. There are several problems with using a simple t-test here. The underlying returns are not normally distributed, so they are only valid asymptotically. Second, the Buy-All, Sell-All measurements are based on samples with a large set of common values. These are far from independent draws. The bootstrap adjusts for both of these problems.

series randomly drawn with replacement from the actual returns series. From these simulated time series a new geometric random walk price series is produced. This allows testing a null hypothesis where returns follow the same unconditional distribution as actual returns, but all dependence in the series is destroyed.[5] The p-values report the fraction of bootstrap simulations which give values as large as that from the original sample.

For the entire sample, and the earlier subsample, the results confirm those of BLL. The buy period means are larger, and the sell period means are smaller. This agrees for all three measures using both the t-statistics, and the bootstrap p-values. In the later sample the results change dramatically. Not only is the buy return no longer significantly larger than the sell return, it is actually less than both the sell return, and the unconditional mean. The t-statistics, and the bootstrap p-values appropriately caution us that these are probably insignificant. However, the fact remains that there is no longer an important difference in conditional means across periods.

A final distinction across the samples is given in the column labeled, Buy Fraction. This reports the fraction of days which are labeled as a buy period by the rule. The dramatic run up in the stock market in the later period is represented here by a large increase in the buy periods. It moves from 62% for the entire sample, to a dramatic 81% in the last subsample. This along with the large increase in mean return gives an indication that something unusual has been going on during the last 10 years.

Table 2: *Conditional Means*

Series	Buy-Sell (%)	Buy-All (%)	Sell-All (%)	Buy Fraction
1897-1999(Feb)	0.061	0.023	-0.038	0.622
	(4.60)	(2.22)	(-3.10)	
	[0.00]	[0.00]	[1.00]	
1897-1986	0.066	0.026	-0.040	0.599
	(4.73)	(2.36)	(-3.09)	
	[0.00]	[0.00]	[1.00]	
1988-1999(Feb)	-0.048	-0.009	0.039	0.807
	(-1.12)	(-0.37)	(0.922)	
	[0.84]	[0.80]	[0.15]	

Conditional mean returns during buy and sell periods using the 150 day moving average rule. Buy-Sell is the difference between buy and sell period means. Buy-All and Sell-All are the differences between the buy period and the unconditional mean, and the sell period and the unconditional mean. Numbers in parenthesis are t-statistics on the means, and numbers in brackets represent the fraction of 1000 random walk bootstrap simulations generating an equivalent conditional mean as large as the sample.

To get a more detailed picture of the dynamics of how the conditional means are changing figure 1 shows a rolling window of the simple t-test performed in table 2. A 5 year window is moved across the entire

[5] See Brock et al. (1992) and LeBaron (1998) for financial applications. A very nice summary for finance is contained in Maddala & Li (1996). The bootstrap methodology is due to Efron (1979), and a useful reference is Efron & Tibshirani (1993).

sample, and the Buy-Sell t-test is recorded over each window. The window is moved in half year increments, so there is a large overlap between windows. The figure is important in presenting several different features of the data. First, it is clear that something unusual appears to be happening over the most recent time periods. Not only is the mean difference negative, but it is currently recording values that are historically small given the last 100 years of data. It is also interesting to note the relative variability in the results. The values appear to take long swings into the positive and negative regions.

4 Conditional Variances

Results in BLL moved beyond conditional means and tested conditional variances as well. These require the use of the bootstrap for determining statistical significance.[6] Table 3 reports the ratios of the estimated variances during buy and sell periods, and relative to all periods. The first row shows that the ratio of the variances between buy and sell periods is only 0.43, indicating that the buy variance is less than half that of the variance during sell periods. The two values below it in brackets are the bootstrap p-values for two different null models. First, the random walk is repeated as done in the previous section. Second, since conditional variances are now a key part of what is going on, a simple GARCH(1,1) model is fitted to the returns series. Normalized residuals from this are scrambled and used to build representative GARCH(1,1) data.[7] The values of 1 indicate that none of the simulated models can generate a variance ratio as large as that in the data. This holds for all three variance ratios. For the Sell/All ratio, remember that since this is unusually large the simulated p-value is now zero, indicating that all the simulated values were less.

Looking across the subsamples a similar pattern is observed. Most interesting, is that in sharp contrast to table 2 the variance differences do not change going into the most recent 10 year period. The ratio of the buy to sell variances is 0.51 in the last 10 year period which is very close to that for the entire sample. The simulations again indicate that the differences are significant. For conditional variances the pattern of lower variances during buy periods has remained relatively constant over the entire sample, unlike the pattern for conditional means.

Table 4 repeats the results of the previous table for absolute deviations. The variance is now replaced with the expected absolute deviation, $E|r_t - E(r_t)|$. This is estimated using the appropriate sample moments

[6] It is possible that tests for conditional variances could have been developed using F-test like objects, but the nonnormality of the daily returns series makes this impossible.

[7] GARCH models developed by Bollerslev (1986), and related to the ARCH models of Engle (1982) are commonly used in finance to model movements in conditional variances. Bollerslev, Engle & Nelson (1995) and Bollerslev, Chou, Jayaraman & Kroner (1990) are useful surveys of this large literature.

Table 3: *Conditional Variance Ratios*

Series	Buy/Sell	Buy/All	Sell/All
1897-1999(Feb)	0.430	0.666	1.548
RW bootstrap	[1.00]	[1.00]	[0.00]
GARCH bootstrap	[1.00]	[1.00]	[0.00]
1897-1986	0.451	0.671	1.499
RW bootstrap	[1.00]	[1.00]	[0.00]
GARCH bootstrap	[1.00]	[1.00]	[0.00]
1988-1999(Feb)	0.516	0.847	1.642
RW bootstrap	[1.00]	[1.00]	[0.001]
GARCH bootstrap	[1.00]	[0.999]	[0.00]

Buy/Sell shows the ratio of the conditional variances during buy and sell periods. Buy/All, and Sell/All are the ratios with the unconditional variances. Numbers in brackets are, as labeled, random walk, and GARCH(1,1) bootstraps p-values, giving the fraction of 1000 simulations generating a value as large as that in the data.

during buy and sell periods. This is an important robustness check for the previous results. They may have been driven by a few large outliers causing some of the variance estimates to become very large. Absolute deviations are less sensitive to outliers. The table repeats all of the results for the conditional variances exactly, indicating that outliers in any of the subsamples were probably not the cause.

Table 4: *Conditional Mean Absolute Deviation Ratios*

Series	Buy/Sell	Buy/Mean	Sell/Mean
1897-1998	0.697	0.859	1.230
RW bootstrap	[1.00]	[1.00]	[0.00]
GARCH bootstrap	[1.00]	[1.00]	[0.00]
1897-1986	0.698	0.852	1.221
RW bootstrap	[1.00]	[1.00]	[0.00]
GARCH bootstrap	[1.00]	[1.00]	[0.00]
1988-1999-Feb	0.740	0.937	1.266
RW bootstrap	[1.00]	[1.00]	[0.001]
GARCH bootstrap	[1.00]	[0.999]	[0.00]

Buy/Sell shows the ratio of the conditional absolute deviations during buy and sell periods. Buy/All, and Sell/All are the ratios with the unconditional absolute deviations. Numbers in brackets are, as labeled, random walk, and GARCH(1,1) bootstraps p-values, giving the fraction of 1000 simulations generating a value as large as that in the data.

The changes in conditional variance reported here are related to the well known "leverage effect" originally documented in Black (1976).[8] Table 5 provides a quick check as to whether the trading rule based forecast is only picking up information coming from the previous day's rise or fall. The table reports conditional variances for $t+1$ both for all buy and sell periods, and further conditions these on the sign of the previous day's return. The table shows that conditioning on the previous day's return does not eliminate the difference

[8] See also (Nelson 1991), and (Bollerslev et al. 1995) for more information and modeling techniques.

in volatility between buy and sell periods in either the full sample, or the recent subperiod. It appears that there is still some impact from r_t for either subset, but it is relatively small. Although no statistical tests are provided here, this table is suggestive that the moving average is providing more information than that coming from the previous day alone in terms of variance forecasts.

Table 5: *Conditional Variances*

Series	r_t	Buy Variance (%)	Sell Variance (%)
1897-1999	All	0.0077	0.0179
	$r_t \geq 0$	0.0068	0.0153
	$r_t < 0$	0.0088	0.0199
1988-1999 (Feb)	All	0.0066	0.0128
	$r_t \geq 0$	0.0056	0.0109
	$r_t < 0$	0.0078	0.0146

Variances for r_{t+1} conditioned on technical signal (column), and sign of previous days return (row).

Both this section and the previous one imply that the predictability in returns might be used in a dynamic trading strategy. Table 6 gives information on the unconditional Sharpe ratios from following several simple dynamic strategies over the different time periods. The numbers presented are annual Sharpe ratios (Sharpe 1994). Buy and Hold follows a buy and hold strategy. Buy/Sell takes a long or short position depending on whether a buy or sell signal is given.[9] Buy corresponds to a strategy of buying during buy periods, and holding a risk free asset earning a 3 percent return during sell periods. The Sharpe ratio is estimated using zero variance during the sell periods. The column labeled buy uses the unconditional daily variance as the variance estimate in the buy period, and the column labeled buy/buy variance uses the conditional variance during buy periods. This latter measure should be the true Sharpe ratio for this strategy, but the other measure is useful for comparison. The table shows that for the entire sample the strategy does outperform buy and hold, and it would best be implemented by activating only during buy periods. Finally, the reduction in conditional variance during buy periods has an impact on the Sharpe ratio. The second row shows that none of these results hold during the last 10 years. The Sharpe ratios are actually in a range that might be interesting, but they are all negative as indicated buy the earlier results on conditional means.

Table 6: *Sharpe Ratios*

Series	Buy and Hold	Buy/Sell	Buy	Buy/Buy Variance
1897-1999	0.123	0.286	0.382	0.462
1988-1999 (Feb)	0.776	-0.053	-0.495	-0.518

[9] This is done primarily for comparison. It is unlikely that this strategy would have been feasible over much of the time period since it would have been difficult to short the Dow.

5 Momentum Strategies

It is clear that the moving average strategy is not looking for anything more complicated than a simple persistence in the returns series. This might be a persistence that is hard to see using traditional autocorrelations.[10] A slightly simpler approach to setting up trading signals is to look at returns over the past 150 days rather than using the moving average price comparisons.[11]

Table 7 shows the results for a 150 day momentum strategy along with the moving average strategy. This strategy records a buy at time t, if $P_t \geq P_{t-150}$, and a sell otherwise. For the entire sample the two strategies are strikingly close to each other. Over the more recent subperiod, the momentum strategy reverses signs as does the moving average, but it is actually significantly negative for the buy-sell difference.

Table 7: *Conditional Means: Momentum Comparison*

Series	Method	Buy-Sell (%)	Buy-All (%)	Sell-All (%)
1897-1999(Feb)	Moving Average	0.061	0.023	-0.038
		(4.60)	(2.22)	(-3.10)
	Momentum	0.056	0.021	-0.035
		(4.21)	(2.04)	(-2.86)
1988-1999(Feb)	Moving Average	-0.048	-0.009	0.039
		(-1.12)	(-0.37)	(0.922)
	Momentum	-0.122	-0.018	0.103
		(-2.55)	(-0.73)	(2.18)

Conditional mean returns during buy and sell periods using the 150 day moving average and momentum rules. Buy-Sell is the difference between buy and sell period means. Buy-All and Sell-All are the differences between the buy period and the unconditional mean, and the sell period and the unconditional mean. Numbers in parenthesis are t-statistics on the means.

Table 8 repeats the results for conditional variances using the momentum conditioning information. This table shows that there is little change going from the moving average strategy to the momentum strategy. For example, the buy/sell ratio goes from 0.43 for the moving average to 0.44 for the momentum measure over the entire sample. Similar features are given for the other measures, and both subperiods appear to be quite similar. These results suggest that these two technical rules may be very similar in practice, and there is nothing particularly special or important about the moving average representation.[12]

[10] This is related to the more sensitive tests for random walk behavior developed in (Lo & MacKinlay 1988). Also, processes with these properties have been modeled by (Taylor 1992) and (LeBaron 1992).

[11] Acar (1993) shows how to map technical rules from price space into returns space. The moving average rule can be formulated as a weighted sum of past returns, but the momentum strategy is a simple sum of past returns. It is an interesting experiment to see if this rule picks up anything different from the moving average rules. Also, see Chan, Jegadeesh & Lakonishok (1996) and Jegadeesh & Titman (1993) for examples from return cross sections.

[12] These results are consistent with the findings in Acar & Lequeux (1996) which find that even for a random walk the correlation between a moving average and momentum strategy is 0.6885.

Table 8: *Conditional Variance: Momentum Comparison*

Series	Method	Buy/Sell	Buy/Mean (%)	Sell-Mean (%)
1897-1999(Feb)	Moving Average	0.430	0.666	1.548
RW bootstrap		[1.00]	[1.00]	[0.00]
GARCH bootstrap		[1.00]	[1.00]	[0.00]
1897-1999(Feb)	Momentum	0.442	0.682	1.542
RW bootstrap		[1.00]	[1.00]	[0.00]
GARCH bootstrap		[1.000]	[1.00]	[0.000]
1988-1999(Feb)	Moving Average	0.516	0.847	1.642
RW bootstrap		[1.00]	[1.00]	[0.00]
GARCH bootstrap		[1.00]	[1.00]	[0.00]
1988-1999(Feb)	Momentum	0.622	0.914	1.468
RW bootstrap		[1.00]	[1.00]	[0.00]
GARCH bootstrap		[1.00]	[0.99]	[0.00]

Buy/Sell shows the ratio of the conditional variances during buy and sell periods using the 150 day momentum strategy. Buy/All, and Sell/All are the ratios with the unconditional variances. Numbers in brackets are, as labeled, random walk, and GARCH(1,1) bootstraps p-values, giving the fraction of 1000 simulations generating a value as large as that in the data.

6 Conclusions

This paper is a short followup to Brock et al. (1992) examining what has happened to some of the strategies they used in the intervening years. Other researchers have already shown dramatic changes in the conditional means, and those are repeated here. This paper performs further diagnostics by checking the variance relationship. In contrast to the means they appear to be quite consistent over time, and robust to using absolute value volatility measures. Finally, it is shown that many similar results could be obtained using a simple momentum type of trading strategy.

On the practical side of using trading rules, this paper shows that using them to forecast conditional means can be very dangerous in the current market. This danger is above and beyond the usual problems of transactions costs, and issues related to actually implementing a strategy. However, it remains to be seen if the strategy's volatility predicting capabilities could offer an edge in either trading options, or risk management. This paper suggests that such a study might be very interesting, given that conditional variance predictability is robust across time periods.

Figure 1 makes a dramatic visual point about the stability of technical trading rules. It opens deep philosophical questions about data snooping, and stationarity. Has something about the dynamics of stock prices changed over the past 10 years, or was the original trend following strategy mined out of the previous 90 years of data? Results in (Sullivan et al. 1999) suggest that it was a change in the data, since their test attempts to adjust for data mining in the previous sample. However, no test for data mining is perfect, as it depends on simulating the snooping process that might have been occurring. No formal tests can be performed to answer this question, but figure 1 along with some historical facts about technical trading that were given in BLL appear to defend the conclusions of Sullivan et al. (1999). BLL were careful to use rules that had existed in the technical trading community for some time, and did not try to perform any extra parameter tuning over their samples. Some of these rules have been in use since the early part of the century. Given that they were not "tuned" to the previous 90 year sample, the results over the past 10 years are even more interesting. This arbitrary feature of the data has changed dramatically, and in this context it looks impossible that the past 10 years could be a draw from any 10 year period in the 90 year history.[13] While it is impossible to ever completely avoid the problems of data snooping the results here suggest that something has changed dramatically.

A final result of this short study suggests that the rules that were used in Brock et al. (1992) could have been replaced with simpler ones. Simple momentum based strategies show similar performance using both measures of predictability. Simplicity and parsimony is just as much a virtue for technical trading rules as it is for other more traditional time series methods, so it is important to see that a simpler rule might have done just as well. Many technical rules use many more complex combinations of moving average patterns, and it would be interesting to find out what the value added of these is. However, in the nonstationary world suggested by these results, robustness may be a far greater virtue than previously thought.[14]

The results reported in Brock et al. (1992) have clearly changed over recent years. However, their results on predicting conditional variance remain stable. The causes of the first change remain an interesting open question. They may have to do with technology, better price information, and lower transaction costs, or possibly a greater attention is now given to technical trading rules. In all cases the changes in the profitability of these dynamic strategies provides an important piece of information on how markets function. If traders have indeed traded the profits away, then an interesting study would be to look at the volatility side of the picture in a similar light. Is there a dynamic strategy that would push the conditional variances toward eachother? This is a much more complicated question than for the means, but it would be a very interesting question to answer.

[13] Remember, that the data snooping counter to this would be that the rules were tuned over the 90 year previous history to maximize the conditional buy-sell difference. In this case it is not so amazing that the last 10 years look different.

[14] See (Bookstaber 1999) for examples of robustness and course decision rules in finance.

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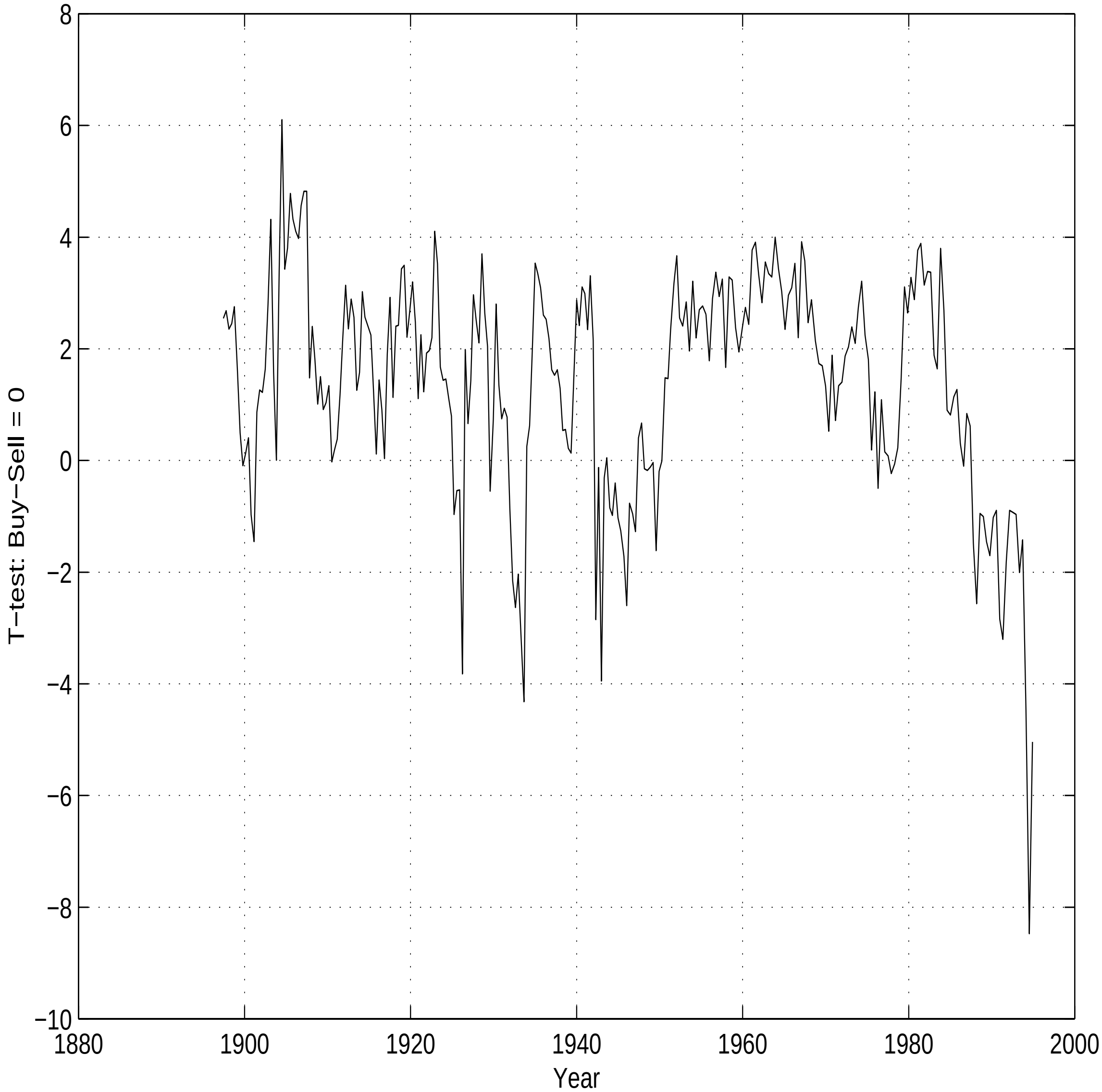

Figure 1: *Rolling T-test: Buy-Sell difference, 5 year rolling window*