Trading profitability of technical strategies in individual stocks

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Abstract

This paper investigates the technical rules' profitability in 15 individual stocks listed in NYSE. By using 5-minute returns from 6 months sample from October to December in 2001 and from April to June in 2002, White's (2000) Reality Check bootstrap procedure is applied to 3,807 technical rules for correcting the data-snooping problem. The results show that none of the 15 stocks gives profitable trading strategies, implying that the profitable chances tend to disappear within 5 minutes.

Keywords: Technical trading, high frequency data, reality check bootstrap

1. Introduction

This paper examines the profitability and its statistical significance of intraday technical trading across 15 individual stocks listed in the New York Stock Exchange (NYSE). The NYSE Trades and Quotes (TAQ) dataset from October to December in 2001 and from April to June in 2002 is used with 5 minutes intervals, and 3,807 technical trading rules from filter, moving average, trading range break, and channel breakouts are examined. White's (2000) Reality Check bootstrap procedure is applied to the large sets of technical rules, in order to find the profitability and correct the data-snooping problem, which might occur when we find profitable rules due to pure luck.

There has been much academic work on technical trading strategies, but the conclusions on whether the technical trading is profitable are still mixed. Some of the previous literature shows that the technical rules are not successful for predicting return dynamics in more recent periods. For example, Sullivan, Timmermann, and White (1999) find that the technical rules are profitable in their dataset of the Dow Jones Industrial Average only before the stock market crash in 1987, but the profitability disappears during the periods

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of 1987-1996. Qi and Wu (2006) show that technical rules are still significantly profitable in 7 currency pairs of the foreign exchange markets.

However, most of those papers have focused on daily data, so those results would investigate the profitable opportunities from technical strategies when investors trade at daily trading horizons. Osler (2003) demonstrates that order clustering in the order book can explain two popular predictions from technical trading analyses (trends tend to be reversed around the round numbers while those tend to be intensified once the rate penetrates the round numbers). Her result implies the presence of predictable variations in return series in ultra high-frequency data.

There have been quite few papers analyzing trading profits from technical indicators by using tick-by-tick data. Motivated by that, this paper utilizes high frequency data with 5 minutes intervals to test the profitability of technical strategies. Marshall et al (2008) also uses the 5 minutes intervals of the transactions data for the Standard and Poor's Depository Receipts (SPDRs). However, they show that none of their 7,846 rules are able to beat the market even after the data snooping problem is corrected, although some profitability maybe expected there because 5 minutes data gives rules more opportunities to transact. Rather than the SPDRs profitability, this paper analyzes the profitability for individual stocks to ask whether traders could be able to make profits if they focus on trading a few stocks so frequently.

In addition to showing the profitability of individual stocks, this paper provides possible explanations on the results of Marshall et al (2008), i.e., why the SPDRs returns may not be profitable. One possible answer is that if some of the stocks would produce successful trading rules while some others would not, we would conclude that the technical rules in the composite returns are not profitable because the profitability for each stock is just averaged out. However, this paper shows that those are not profitable because none of the stocks produces successful trading rules after correcting the data-snooping biases.

Section 2 introduces the TAQ dataset, and shows how I clean and manipulate it before using it. After constructing the return series of 5-minute interval, I will show the summary statistics for 15 stocks. Section 3 describes the White’s Reality Check bootstrap procedure. Section 4 introduces technical trading rules, which are used in this paper. Section 5 conducts empirical tests and the last section concludes.

2. Data and Summary Statistics

I examine transaction data on 15 stocks taken from NYSE TAQ (Trade and Quote), which covers six months from October to December in 2001 and from April to June in 2002. There are 129 trading days in total (64 trading days in the 2001 sample and 65 days in the 2002). I chose the 15 stocks from the larger size group in the S&P500 listed companies at that time. The two different periods are chosen to investigate the performance of the technical rules in bull and bear markets. The NYSE composite index is increased by 8.4% from October to December in 2001 while it is decreased by 11.6% from April to June in 2002.[1]

The 5-minute returns are calculated by using the transaction prices recorded from 9:30am (the official start of trading on the NYSE) to 4pm (the official close of trading).[2] I define the returns over the 5-minute interval as:

$$r_{t+1} = \frac{P_{t+1} - P_t}{P_t} \qquad (1)$$

where P_t is the original transaction price series.

Table 1 gives the summary statistics of the return series for all 15 stocks in the two sub-sample periods. The last column gives the averages of each statistic over the 15 stocks. The averages of the sample over 15 stocks are 4,690.5 in the three months in 2001 and 4,777.4 in the 2002 sample. The mean returns are mostly positive in the 2001 sample, while those are negative for most of the stock in the 2002 sample. Those reflect that the economy was in the bull in the 2001 and in the bear for the 2002 sample as shown in the NYSE composite index. These returns are strongly leptokurtic for the entire series and both sub-sample periods. Most of the distributions look skewed to the left (11 stocks in the 2001 sample and 10 stocks in the 2002 show negative skewness). The statistics on kurtosis and skewness imply non-normal distributions for the individual stocks. Serial correlations are generally small and mostly negative for all series. The first-order autocorrelations are negative for 12 stocks in the 2001 sample and for 9 stocks in the 2002 sample.

[1] I used this NYSE composite index from Datastream.

[2] I do not discard transaction prices that did not occur on the NYSE (Brownlees et al (2006)). Trades for which TAQ's CORR field is equal to either zero or one are included , and trades for which the COND field is either blank or equal to B, J, K, or S are analyzed (Boehmer et al (2005)). I eliminate trades with non-positive prices (Boehmer et al (2005)). I exclude a trade if its price is greater (less) than 150% (50%) of the price of the previous trade (Bessembinder (1999)). I cumulate any trades that were recorded with the same time stamp into one trade. To do this sum the total volume of the trades, attributed it to the first trade, and then removed the other trades from the sample (Engle and Patton (2004)). Any trades that were recorded to have occurred before 9:30am (the official start of trading on the NYSE) or after 4pm (the official close of trading) were removed, and I consider all trades that occur before the first quote of the day to be indeterminate (Engle and Patton (2004)). I ignore the first and last few trades of a day.

Table 1: Descriptive Statistics of Returns

Panel A: Oct.-Dec. 2001

	AIG	T	BMY	KO	DD	XOM	GE	GM	HWP	IBM	JNJ	MRK	PFE	PG	WMT	***Average***
N	4712	4754	4730	4696	4674	4783	4854	4621	4002	4813	4737	4723	4789	4692	4777	***4690.5***
Meanx1000	0.008	-0.005	-0.018	0.005	0.030	0.005	0.020	0.033	0.073	0.060	0.018	-0.025	0.001	0.021	0.036	***0.017***
Std.x1000	1.831	3.448	2.254	1.713	2.299	2.279	2.612	2.471	4.033	1.868	1.593	2.077	1.881	1.695	1.972	***2.268***
Skewness	-0.383	6.788	-0.290	-0.430	-0.356	-0.398	0.333	-0.801	-0.553	1.299	-1.104	-3.480	-0.433	1.574	-0.091	***0.112***
Kurtosis	21.564	352.499	17.498	26.580	21.965	14.553	23.662	60.176	19.450	38.298	16.858	89.721	14.125	35.405	9.552	***50.794***
rho(1)	0.010	-0.085	-0.055	-0.040	-0.033	-0.103	-0.085	0.011	0.039	-0.017	-0.115	-0.028	-0.076	-0.101	-0.094	***-0.051***
rho(2)	-0.030	-0.011	-0.034	-0.009	-0.034	-0.034	-0.043	0.038	0.043	-0.027	-0.020	-0.024	-0.021	-0.024	-0.005	***-0.016***
rho(3)	-0.013	-0.056	-0.008	0.008	-0.025	0.000	0.022	0.011	0.010	0.010	0.008	0.011	-0.017	-0.008	-0.006	***-0.004***
rho(4)	-0.001	-0.039	-0.005	0.014	0.025	-0.009	-0.022	0.025	0.018	-0.002	-0.023	0.017	-0.014	-0.027	0.051	***0.000***
rho(5)	-0.011	0.015	-0.002	0.011	0.000	0.013	-0.011	0.008	0.038	-0.020	0.013	0.012	0.015	0.005	0.035	***0.008***

Panel B: April -June 2002

	AIG	T	BMY	KO	DD	XOM	GE	GM	HWP	IBM	JNJ	MRK	PFE	PG	WMT	***Average***
N	4773	4834	4843	4775	4735	4850	4927	4766	4106	4880	4838	4810	4867	4810	4847	***4777.4***
Meanx1000	-0.007	-0.080	-0.077	0.016	-0.009	-0.015	-0.046	-0.022	-0.026	-0.069	-0.039	-0.024	-0.020	0.001	-0.014	***-0.029***
Std.x1000	2.029	3.284	4.112	1.637	2.204	1.823	2.645	1.892	2.709	2.903	1.855	2.034	2.415	1.459	2.243	***2.350***
Skewness	0.695	-0.816	-20.791	-0.402	-0.264	-0.630	-0.206	-0.344	0.792	-6.743	-0.368	-1.471	0.335	0.290	1.817	***-1.874***
Kurtosis	11.745	27.667	993.567	9.505	25.978	23.028	23.647	30.369	24.599	309.750	12.997	27.731	29.104	9.313	36.191	***106.346***
rho(1)	0.013	0.001	0.012	-0.086	-0.046	-0.109	-0.006	0.102	0.004	0.006	-0.046	-0.026	-0.027	-0.031	-0.019	***-0.017***
rho(2)	-0.008	-0.005	0.006	0.011	-0.032	-0.050	-0.015	0.021	0.036	-0.032	-0.013	0.000	-0.020	0.020	-0.010	***-0.006***
rho(3)	-0.021	0.017	-0.033	0.002	-0.029	0.016	-0.004	-0.008	0.048	0.023	-0.028	0.003	-0.004	-0.030	-0.029	***-0.005***
rho(4)	-0.009	0.007	-0.004	-0.017	-0.003	-0.002	0.013	-0.024	0.011	-0.006	-0.023	-0.018	-0.019	-0.035	0.015	***-0.008***
rho(5)	-0.002	0.008	-0.057	0.010	0.008	0.004	-0.042	-0.019	0.025	0.014	-0.006	0.032	-0.005	-0.038	0.013	***-0.004***

Company codes: AIG (American International Group), T (AT&T), BMY (Bristol Myers Squib), KO (Coca Cola), DD (DuPont), XOM (Exxon), GE (General Electric), GM (General Motors), HWP (Hewlett Packard), IBM (International Business Machines), JNJ (Johnson & Johnson), MRK (Merck), PFE (Pfizer), PG (Procter and Gamble), and WMT (Wal-Mart).

3. The While's Reality Check

As shown in Table 1, the returns do not follow normal distribution. This result suggests that the t-test cannot be applied for testing profitability of technical trading rules. As Brock, Lakonishok, and LeBaron (1992) argued, the profitability should be evaluated by the bootstrap methodology. This paper uses the White's Reality Check bootstrap for dealing with the non-normal ultra high-frequency data as well as accounting for the potential data snooping biases.

Based on the methods of Diebold and Mariano (1995) and West (1996), White (2000) presents the test procedure on whether a given model has predictive superiority over a benchmark model after accounting data snooping effects. This White's (2000) Reality Check can be applied for testing the profitability of the best trading rule. It tests the null hypothesis that the profit generated by the best trading rule does not exceed that of a benchmark strategy. It gives an estimate of the true and nominal p-values for the null by bootstrapping simulations. The true p-value is the statistic, which is adjusted for data snooping by taking into account the entire universe of rules where the best rule is selected. So, this p-value indicates the significance of the profitability of the best rule in the universe of the whole trading rules. The nominal p-value is the significance simulated with the sample only in the best trading rule. So, this value ignores the effect of the data snooping. Therefore, the difference between the true and nominal p-values represents the magnitude of the data-snooping biases.

Applying the White's Reality Check procedure to the Dow Jones Industrial Average and S&P 500 datasets, Sullivan, Timmerman, and White (1999) provide empirical evidence on the profitability of the best trading rule among a wide set of trading rules. I follow their set-up for testing the profitability. The performance statistic for each trading rule is given by:

(2) $$\bar{f}_k = T^{-1}\sum_{t=1}^{T} f_{k,t+1} \quad \text{k=1,….,M}$$

where M is the number of technical trading rules, and T is the number of trading periods. $f_{k,t+1}$ is the performance measure observed at t+1. In my application, M is equal to 3,807. The performance measure $f_{k,t+1}$ is defined as:

(3) $$f_{k,t+1} = \ln\left[1 + r_{t+1}S_k\left(P_t, \beta_k\right)\right] - \ln\left[1 + r_{t+1}S_0\left(P_t, \beta_0\right)\right]$$

where P_t is the original price series. $S_k(\bullet)$ and $S_0(\bullet)$ are signal functions that map the price information into trading signals, which take 1 which represents a long position, -1 which represents a short position, and 0 which represents a neutral position. So, the performance measure, $f_{k,t+1}$, is the excess returns of a trading rule, k, from a benchmark return. The benchmark returns is the returns from long position for all periods.

I test the null hypothesis that the returns from the best technical trading rule are no better than those from the benchmark strategy. In other words,

$$H_0 : \max_{k=1,....,l} \{\bar{f}_k\} \leq 0$$

The rejection of the null gives us an implication that the best trading rule produces higher performance than the benchmark strategy.

In White (2000), the null hypothesis can be evaluated by applying the stationary bootstrap of Politis and Romano (1994) to the observed value of $f_{k,t+1}$. I will derive the Reality Check p-value to test that the best rule has superior performance than the benchmark. First, for each trading rule, I resample $f_{k,t+1}$ with replacement B times, and denote the resampled series as $f^*_{k,t+1,b}$ (b=1,….,B). Second, I calculate the average of the bootstrap returns as:

$$\bar{f}^*_{k,b} = T^{-1} \sum_{t=1}^{T} f^*_{k,t,b} \qquad \text{b=1,….,B}$$

I set B=500. Then I construct the following statistics:

$$\bar{V}_m = \max_{k=1,....,M} \left[\sqrt{T}\, \bar{f}_k \right]$$

$$\bar{V}^*_{M,b} = \max_{k=1,....,M} \left[\sqrt{T} \left(\bar{f}^*_{k,b} - \bar{f}_k \right) \right] \qquad \text{b=1,….,B}$$

The White's Reality Check p-value is obtained by comparing $\bar{V}_m$ and $\bar{V}^*_{M,b}$. In particular, I sort out $\bar{V}^*_{M,b}$ (b=1,…,B) and denote it as:

$$\bar{V}^*_{S,(1)}, \bar{V}^*_{S,(2)}, ..., \bar{V}^*_{S,(B)}.$$

I then find N such that $\bar{V}^*_{S,(N)} \leq \bar{V}_m < \bar{V}^*_{S,(N+1)}$. The White's Reality Check p-value is given as:

$$p - value = 1 - N/M$$

I choose the smoothing parameter equal to 0.1.

4. Technical Trading rules

The White's Reality Check evaluates the performance of the best trading rule among the wide set of the trading rules. So, I first introduce the trading rules employed in this paper. I consider the following four types of trading rules, which are often used in previous academic papers on technical trading: filter rules, moving averages, trading range break, and channel breakouts. Total number of the rules considered in this paper is 3,807. Each of the rules is described as follows.

The standard x percent filter rule is defined as follows. A buy (sell) signal is extracted if the price of a particular security increases (decreases) by at least x percent from the subsequent low (high). Once a buy (sell) signal is observed, traders buy (sell) and hold (go short) until the next sell (buy) signal is extracted. The subsequent low (high) is the lowest (highest) price achieved when taking short (long) position. In addition to the standard filter rule, I consider following versions of filter rules. First, I use an alternative definition on high (low), which calculates highest (lowest) price over the e previous periods excluding the current price. The second version defines the rule that generates a buy (sell) signal when the price increases (decreases) by at least x (y) percent from the subsequent low (high). Third, following Brock, Lakonishok, and LeBaron (1992), once a signal is extracted according to the x percent filter rule, a given long or short position is held over c periods, ignoring all other signals observed during that time.[3]

The standard moving average (MA) rule gives a buy (sell) signal when the price exceeds (penetrates downward) the moving average over n periods. Once a buy (sell) signal is observed, traders hold long (short) position until the next sell (buy) signal is extracted. Different versions of moving average rules are also considered. First, a buy (sell) signal is observed when a fast moving average exceeds (penetrates downward) a slow moving average where the slow moving average is the average over longer periods than the fast moving average. Second, a fixed band filter is imposed to the standard MA rule. In other words, traders observe a buy (sell) signal when the price (or a fast MA) exceeds a MA (or a slow MA) by a fixed multiplicative amount, b. Third, the time delay filter is considered. The signal is actually observed by traders after d periods. So, traders take an action only in d periods after the signal is extracted. Fourth, traders take position for c periods, while they ignore any signal during those periods.[4]

[3] The parameter values are given as follows. x=0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, and 0.5. y=0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, and 0.2. e=1, 2, 3, 4, 5, 10, 15, and 20. c=5, 10, 25, and 50. Assuming that y is less than x, there are 497 filter rules.

[4] The parameter values for moving average rules are given as follows. n=2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, and 250. m=105, which is the number of fast-slow combinations of n. b=0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, and 0.05. d=2, 3, 4, and 5. Total number of moving average rules is 2,040.

A buy (sell) signal is produced in a simple trading range break rule when the price exceeds (is less than) the maximum (minimum) price over the previous *tb* periods. I also consider a fixed multiplicative band filter, *b*, and a time delay filter, *d*. In addition, traders hold positions for *c* periods, ignoring all signals produced during those periods.[5]

The last type of the trading rule is channel breakouts. Traders buy (sell) and hold a long (short) position when the price exceeds (becomes less than) the channel where a channel is produced when the high over the previous *cb* periods is within *xb* percent of the low over the previous *cb* periods. In addition, different versions of the channel breakout rules are analyzed by imposing a fixed multiplicative band filter, *b*, a time delay filter, *d*, and a fixed number of periods that a position is held, *c*.[6]

5. Empirical Results

Table 2 summarizes the performances of the best rule in the 15 stocks. Moving average rules are selected for 13 stocks in the 2001 sample and for 10 stocks in the 2002 sample. Filter rules are the best rules for only one stock in the 2001 sample and 2 stocks in the 2002 sample. Only one stock selects trading range break rule in the 2001 sample, but 3 stocks chose it in the 2002 sample. Channel breakouts are not selected in both of the sub-periods. The average numbers of trades are 482.6 in the 2001 sample and 474.8 in the 2002 sample from about 4,700 samples in total in both sub-periods. Mean returns of the best trading rule are all positive but quite small. Those are 0.00008 in the 2001 sample and 0.000088 in the 2002 sample. The nominal p-values are close to zero for all stocks in the 2002 sample, but a bit higher on average in the 2001 sample. The nominal p-values are high for some stocks like IBM (22.8%) and Johnson & Johnson (19.8%) in the 2001 sample, and 24% for Coca Cola in the 2002 sample. However, the most striking result is that almost all of the White's p-values are 1. Even for the stocks which do not show the White's p-value equal to 1, the values are quite close to 1. These results imply that there are severe data-snooping biases in the performance of the best trading rules. Once I account for the effect of the data-snooping, all of the best trading rules are not profitable anymore. These results imply that the stock traders cannot make profits by using technical trading strategies even if they trade individual stocks

[5] *tb*=5, 10, 15, 20, 25, 50, 100, 150, 200, and 250. Total number of trading range break rules is 520.
[6] *cb*=5, 10, 15, 20, 25, 50, 100, 150, 200, and 250. *xb*=0.005, 0.01, 0.02, 0.03, 0.05, 0.075, 0.1, and 0.15. Total number of channel breakouts is 750.

so frequently like every 5 minutes. I also tried the same analyses by using the mid-quote prices prevailing at each transaction. [7] However, I got qualitatively the same results.

Marshall et al. (2008) find that none of their 7,846 trading rules are profitable over 5-minute intervals in their composite index dataset once the data-snooping problem is corrected. The results in this paper would suggest that their results are totally based on the fact that stock traders cannot make any profit even if they focus on trading a few stocks. These results would be consistent with the recent improvements of the market transparency and transaction technology. In most of the stock markets like Tokyo Stock Exchanges, Paris Bourse, or London Stock Exchange, some of the order book information has been available to stock traders without large delay like the last transaction prices, orders around the best prices, and so on. This gives traders more chances to find any profitable opportunities so soon. Actually, since the transactions are immediately conducted through computer systems, the profitable opportunities tend to disappear so quickly. My results imply that as a result of such improvements the profitable chances would disappear within 5 minutes.

6. Conclusion

This paper analyzes and interprets the profitability of 3,807 technical trading strategies for 15 stocks of the larger size firms in NYSE. White's Reality Check bootstrapping procedure is applied to the 5-minute returns series to correct the data-snooping problem. The results say that once I consider the effect of the data-snooping, all 15 stocks do not produce any significant profitable chance to any technical trading rules. Since the trading frequency is 5-minutes here, this implies that stock traders may have to trade so frequently to make profits. In addition, my result would suggest that technical rules are not profitable in trading composite index because those rules are not profitable even in trading individual stocks.

[7] Before using the mid-quote series, I first cleaned the quote data in a following way. All quotes with a primary NYSE listing that did not occur on the NYSE (EX field different from N) are eliminated. I use data denoted N (NYSE) in EX field (Brownlees et al (2006)). I eliminate quotes for which TAQ's MODE field is equal to 4, 5, 7, 8, 9, 11, 13, 14, 15, 16, 17, 19, 20, 27, 28, or 29, and exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask (Boehmer et al (2005)). I use the data with the difference between the bid and the ask, which is smaller than 25% of the quote midpoint. A quote is eliminated if the bid or the ask is greater (less) than 150% (50%) of the bid or ask of the previous quote (Boehmer et al (2005)). Quotes are omitted if the differential between the ask and bid prices exceeds $5 (Bessembinder (1999)). The mid-quote prices are recorded by taking averages of the quoted bid and ask prevailing at each transaction. I follow a 5 seconds rule of Lee and Ready (1991). Any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

Table 2: Performance of the best trading rule

Panel A: Oct.-Dec. 2001

	AIG	T	BMY	KO	DD	XOM	GE	GM	HWP	IBM	JNJ	MRK	PFE	PG	WMT	***Average***
Best Rules	TRB	MA	F	MA	MA	MA	MA	MA	MA	MA	MA	MA	MA	MA	MA	-
Number of trades	226	114	149	42	599	130	709	603	1917	272	918	279	457	281	543	***482.6***
Mean return x 1000	0.057	0.096	0.060	0.060	0.087	0.056	0.073	0.140	0.176	0.084	0.041	0.067	0.055	0.040	0.101	***0.080***
Nominal p-value	0.08	0.028	0.032	0.05	0.096	0.072	0.072	0.012	0.108	0.228	0.198	0.03	0.056	0.26	0.028	***0.09***
White's p-value	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	***1***

Panel B: April -June 2002

	AIG	T	BMY	KO	DD	XOM	GE	GM	HWP	IBM	JNJ	MRK	PFE	PG	WMT	***Average***
Best Rules	F	MA	MA	MA	TRB	MA	MA	MA	MA	MA	F	TRB	TRB	MA	MA	-
Number of trades	104	227	148	317	130	506	457	2334	950	732	140	7	246	138	686	***474.8***
Mean return x 1000	0.065	0.151	0.137	0.040	0.069	0.041	0.102	0.105	0.170	0.101	0.065	0.071	0.093	0.040	0.076	***0.088***
Nominal p-value	0.02	0	0.02	0.24	0.03	0.05	0	0	0	0.01	0	0.02	0.02	0.05	0.02	***0.03***
White's p-value	1	0.998	1	1	1	1	1	1	0.99	1	1	1	1	1	1	***0.9992***

Company codes: AIG (American International Group), T (AT&T), BMY (Bristol Myers Squib), KO (Coca Cola), DD (DuPont), XOM (Exxon), GE (General Electric), GM (General Motors), HWP (Hewlett Packard), IBM (International Business Machines), JNJ (Johnson & Johnson), MRK (Merck), PFE (Pfizer), PG (Procter and Gamble), and WMT (Wal-Mart).
Trading rules: F (Filter rule), MA (Moving averages), TRB (Trading range break), and CB (Channel breakouts).

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