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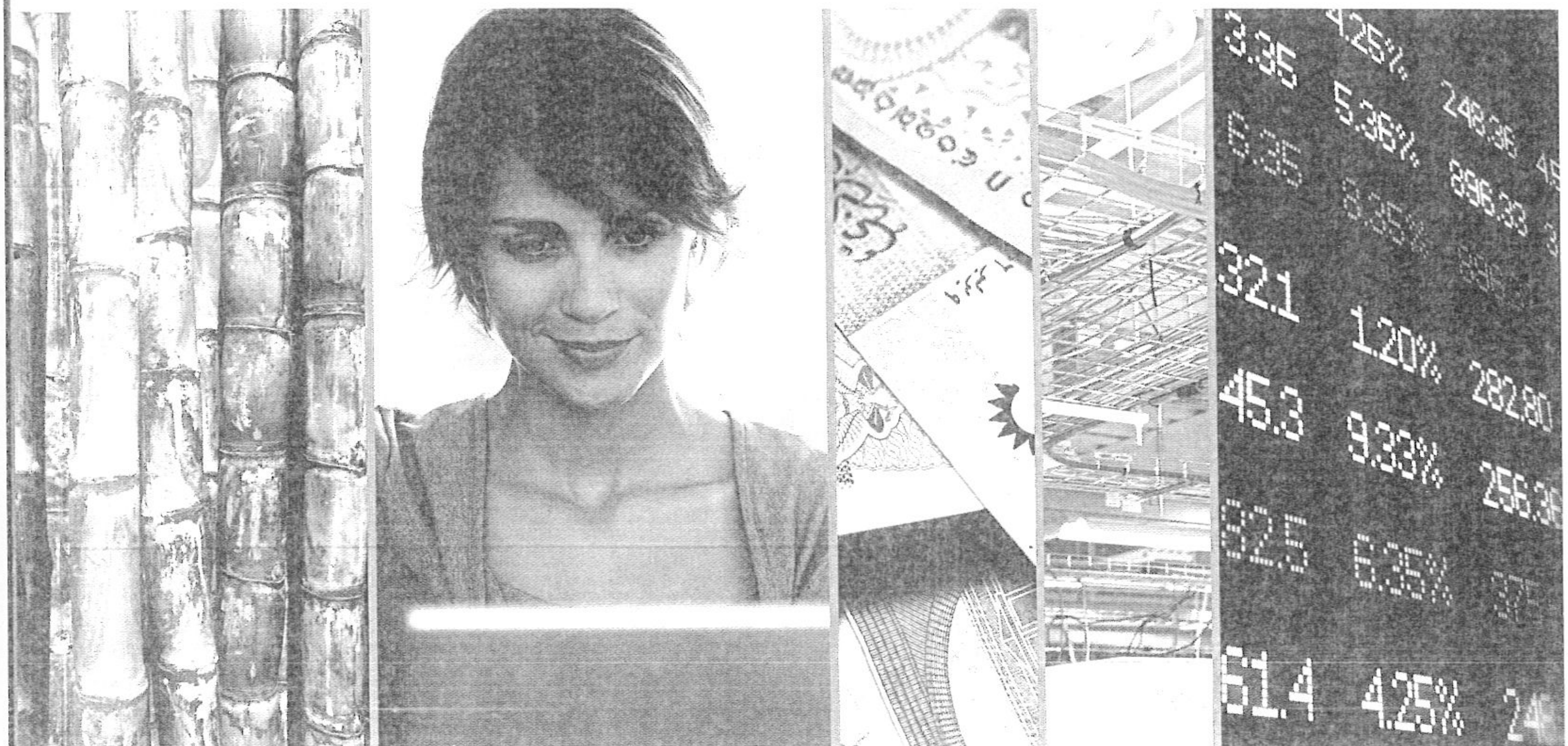

9 **Federal Market Information Technology in the Post–Flash Crash Era: *Roles for Supercomputing***
E. Wes Bethel, David Leinweber, Oliver Rübel, and Kesheng Wu
Lawrence Berkeley National Laboratory

26 **Electronic Markets and Trading Algorithms**
Sunil Wahal, Arizona State University and Dimensional Fund Advisors LP

37 **Price-Pattern Recognition Using a Local Polynomial Regression**
Sheng-Yang Wang and Guoyi Zhang
University of New Mexico

44 **The Failure of Continuous Markets**
Chris Sparrow
Independent Financial Services Professional

48 **Optimal Execution and Alpha Capture**
Adriana M. Criscuolo and Henri Waelbroeck, Aritas Group, Inc.

57 **Whole-Distribution Statistical Process Control in High-Frequency Trading**
Ricky A. Cooper and Ben Van Vliet
Illinois Institute of Technology

69 **Dark Pool DNA: *Improving Dark Pool Assessment***
Ben Polidore, ITG

75 **Can High-Frequency Traders Game Futures?**
Irene Aldridge, ABLE Alpha Trading LTD

83 **Intraday Effects around Directors' Dealings: *Disclosures in Germany and the United Kingdom***
Kaspar Dardas, European Business School

Price-Pattern Recognition Using a Local Polynomial Regression

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Technical analysis is an approach to investing that relies on the idea that the analysis of trends in financial markets can be used to maximize profits through strategic buy and sell decisions. Lo et al. [2000] proposed a systematic and automatic approach to technical pattern recognition using a nonparametric kernel regression. Lo and MacKinlay [2000] concluded in their book that prediction is indeed possible in the equity market. Dawson and Steeley [2003] extended Lo et al's [2000] work on the U.K. stock market and found a weak pattern compared with the pattern of the NYSE and NASDAQ equity market. Wang et al. [2010] implemented a nonparametric kernel regression method in the Chinese stock market. Unfortunately, many technical patterns mentioned in Lo et al. [2000] are not significant in the Chinese stock market.

No doubt, Lo et al. [2000] provided an important foundation for technical analysis by using the statistical tool of nonparametric kernel estimation. However, as pointed out by the authors themselves, "kernel estimators suffer from a number of well-known deficiencies, for instance, boundary bias, lack of local variability in the degree of smoothing, and so on" (Lo et al. [2000]). Specifically, the boundary effects (with large bias and large variance) occur because of discontinuities at the endpoints. With a small sample size of only 38 observations, the boundary points are likely to dominate. A boundary correction can be implemented, but this was not done in the study. Due to the boundary issue, the optimal bandwidth parameter λ from the cross-validation method doesn't work well. In the end, the authors have to multiply it by 0.3 through trial and error and by polling professional technical analysts.

In this research, we propose a complete data-driven technical analysis algorithm with the application of a nonparametric local linear estimator. Our methodology enhances the data-driven estimation of technical pattern recognition with a local linear regression estimator from subjective bandwidth selection with the Nadaraya–Watson (N-W) kernel estimator in Lo et al. [2000]. In a local linear regression, the bias at the boundary and in the interior remain of the same order. The boundary correction occurs automatically without any additional steps. The ultimate goal of this study is to verify that the technical analysis patterns in finance are informative and to identify significant charting patterns for further analysis. We evaluate our proposed algorithm with S&P 500 Index stocks. The results are very informative and promising.

This article is organized as follows. The following section reviews the nonparametric local polynomial regression and generalized cross-validation method. We then describe our proposed technical analysis, provide the data analysis report and present our conclusions.

BACKGROUND

Local Polynomial Regression Estimator

Consider the general nonparametric regression model

$$y_i = u(t_i) + \varepsilon_i, \quad i = 1, 2, \ldots, n, \qquad (1)$$

where $\{\varepsilon_i\}$ is a sequence of independent, identically distributed, random variables with $E(\varepsilon_i) = 0$ and $E(\varepsilon_i^2) = 1$; $u(\cdot)$ is an unknown smooth regression curve; $\{(t_i, y_i)\}$ is a sequence of observations, and t_i has a density function $f(\cdot)$. Stone [1977, 1980, 1982] and Cleveland [1979] systematically studied local polynomial regression. Fan [1992, 1993], Fan and Gijbels [1992] and Ruppert and Wand [1994] studied the local polynomial fitting in more detail.

Suppose that locally the regression function u can be approximated by

$$u(z) \approx \sum_{j=0}^{p} \frac{u^{(j)}(t)}{j!}(z-t)^j = \sum_{j=0}^{p} \beta_j (z-t)^j \qquad (2)$$

for z in a neighborhood of t by using Taylor's expansion, where $\beta_j = \frac{u^j(t)}{j!}$. Equation (2) models $u(z)$ locally by a simple polynomial model. The β_js are chosen to minimize the weighted least-square error

$$\sum_{i=1}^{n} \left\{ y_i - \sum_{j=0}^{p} \beta_j (t_i - t)^j \right\}^2 K\left\{ \frac{(t-t_i)}{\lambda} \right\}$$

where $K(\cdot)$ is the Epanechnikov kernel and λ is the bandwidth. The weighted least-square estimator of β is

$$\hat{\beta} = (\mathbf{X}^T \mathbf{W} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W} \mathbf{Y}$$

where $\mathbf{Y} = (y_1, y_2, \ldots, y_n)^T$, X is an $n \times (p+1)$ matrix with i^{th} row $[1, (t_i - t), \ldots, (t_i - t)^p]$, and $\mathbf{W} = diag\left\{ \frac{1}{h} K\left(\frac{t_i - t}{\lambda} \right) \right\}$.

The N–W kernel estimator is a special case of a local polynomial kernel estimator in the case of fitting degree zero polynomial, that is, constant. The local linear estimator is another special case of a polynomial estimator in the case of fitting degree 1 polynomials $\beta_0 + \beta_1 t$. Fan [1992] proved that the local linear estimator has the same variance as the N–W kernel estimator, but with a smaller bias.

Exhibit 1 displays a comparison between the N–W kernel at boundary and the local linear regression at boundary.

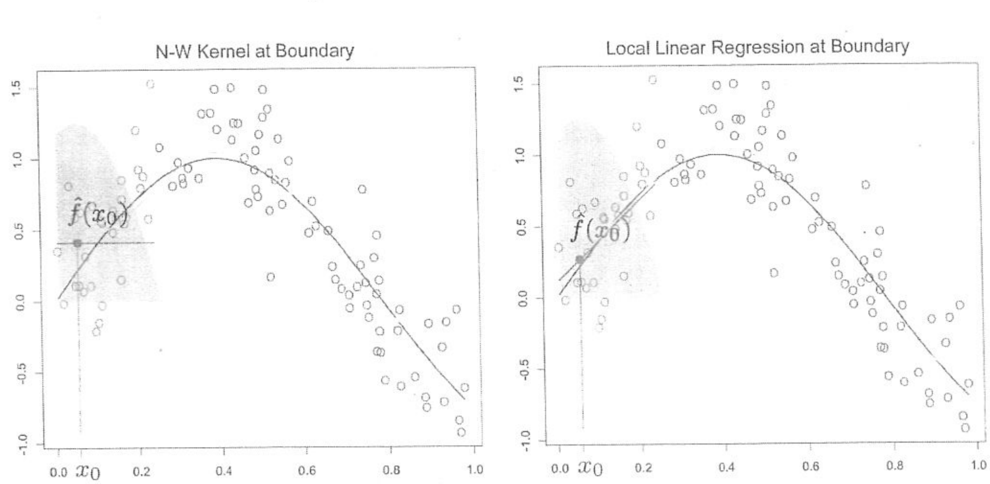
Though both graphs display a smooth curve, at the boundary, we can see the bias in the first graph. This is due to the small number of points within the window when the point to be estimated is close to the boundary. In the local linear regression, the bias at the boundary and in the interior remains of the same order. The boundary correction occurs automatically without any additional steps.

Optimal Bandwidth Selection: Generalized Cross-Validation

The bandwidth parameter or the smoothing parameter, λ, controls the tradeoff between smoothness and

EXHIBIT 1

Boundary Bias Issue (Hasfie et al. [2009], p. 195)



goodness of fit. A bigger λ will give a smooth estimator with a small variance and usually a large bias. On the other hand, if λ is too small, the fitted curve is choppy with a large variance. We want to choose λ in such a way that we can balance the bias and the variance. In other words, we want to fit the data well and control the complexity of the estimator at the same time. The cross-validation (CV) method is used to select the bandwidth in Lo et al. [2000]'s article. The cross-validation method is a frequently used technique for smoothing parameter selection. It derives from the criterion function

$$CV(\lambda) = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \mu_{\lambda(i)}(t_i)\right)^2$$

where $\mu_{\lambda(i)}$ is the estimator μ_λ computed without using the i^{th} observation (t_i, y_i). The process of selecting λ through minimization of $CV(\lambda)$ is called cross-validation. The idea behind the cross-validation method is that the i^{th} observation is treated like an additional observation for prediction and $CV(\lambda)$ measures the quality of predictions. Since there is actually only one observation for each u_i it is no surprise that $CV(\lambda)$ is generally biased for prediction risk.

Generalized cross-validation (GCV) was first proposed by Craven and Wahba [1979] for use in the context of a nonparametric regression. In the 1980s, there were numerous theoretical and practical studies that demonstrated that GCV had a variety of statistical applications (Wahba [1990]). In this section, we review the GCV method that we use to select the bandwidth. GCV is nearly an unbiased estimator of prediction risk.

The vector of fitted values from Equation (1) can be written as

$$\mu_\lambda = \mathbf{S}_\lambda \mathbf{Y} \tag{3}$$

where $\mathbf{S}_\lambda = \mathbf{X}(\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}$ is that matrix as defined in the linear regression and s_{ii} denotes the i^{th} diagonal element of $\mathbf{S}_\lambda$.

The GCV criterion is defined as

$$GCV(\lambda) = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \mu_\lambda(t_i)\right)^2}{\left(\frac{1}{n}\mathrm{tr}(I - S_\lambda)\right)^2}$$

where $\mathrm{tr}(\cdot)$ denotes the trace of the matrix. The GCV criterion can be viewed as a weighted version of $CV(\lambda)$ since

$$\begin{aligned}
GCV(\lambda) &= \frac{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \mu_\lambda(t_i)\right)^2}{\left(\frac{1}{n}\mathrm{tr}(I - S_\lambda)\right)^2} \\
&= \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \mu_\lambda(t_i)}{1 - s_{ii}}\right)^2\left(\frac{1 - s_{ii}}{\frac{1}{n}\mathrm{tr}(I - S_\lambda)}\right)^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \mu_{\lambda(i)}(t_i)\right)^2\left(\frac{1 - s_{ii}}{\frac{1}{n}\mathrm{tr}(I - S_\lambda)}\right)^2 \\
&= CV(\lambda)\left(\frac{1 - s_{ii}}{\frac{1}{n}\mathrm{tr}(I - S_\lambda)}\right)^2
\end{aligned}$$

TECHNICAL ANALYSIS PATTERN

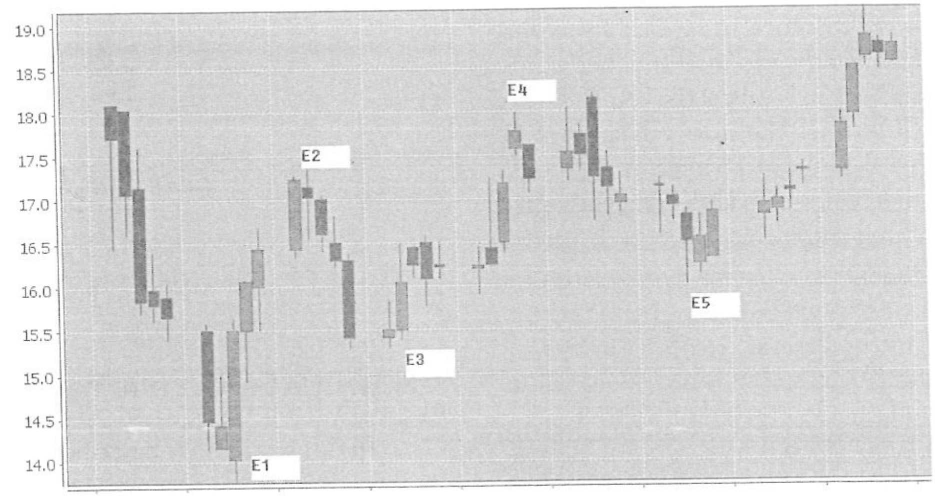
In this section, we describe the proposed technical analysis procedure. The pattern recognition algorithm begins the creation of a window of data to be studied. The rolling window of 38 days employed by Lo et al. [2000] was mirrored.

Suppose that there are T trading days with the sequence of stock closing price $\{P_i\}$ and trading volume $\{V_i\}$, $i = 1, 2, \ldots, T$. The KernSmooth package was utilized to fit the data in each 38-day window $[t, t + l + d - 1]$ using the local linear regression described earlier, where $t = 1, 2, \ldots, T - l - d + 1$. l is set up to be 35 trading days for detecting the pattern, and d is set up to be 3 trading days following the captured pattern. The smoothed data provide the local minimum and maximum values needed to identify the price patterns. We denote these local extrema as $E_1, E_2, \ldots, E_k$ corresponding to $t_1^*, t_2^*, \ldots, t_k^*$ on the occurrences of the trading date. Next we define two technical analysis patterns called moving-up-stream (MUS). The proposed technical analysis pattern is based on the behavioral finance study by Vasiliou et al. [2008] and our trading experience. Besides considering the closing prices, the proposed patterns also detect if the trading volumes are larger than the average of the past 38-day trading periods.

Let E_i be the closing price of the i^{th} local extreme point in the given charting type, $i = 1, 2, \ldots, 5$; V_i be the total trading volume of the day when the i^{th} local extreme point is reached in the given charting type, $i = 1, 2, 3, 4$; and $MA.38$ be the average trading volume of the 38 trading days within the window. Exhibit 2 illustrates the basic shape of the two charting types.

As illustrated by Exhibit 2, the pattern emerges over time, and the noise of daily movements will be smoothed out. The following describes two charting types.

Exhibit 2
Price Pattern



- Charting Type 1:
  E_1 is the minimum
  $E_1 < E_3 < E_5$
  $E_2 < E_4$
  $V_1 > V_3$ and $V_2 < V_4$
- Charting Type 2:
  E_1 is the minimum
  $E_1 < E_3 < E_5$
  $E_2 < E_4$
  $V_1 > MA.38$

Besides considering the closing prices, these two patterns also consider the trading volume. That is, the momentum is lifting up a higher volume. From the investors' perspective, they are waiting and watching for this trading signal. In the whole equity market, they choose to "buy high, sell higher." The bottom line is that the abruptly increasing trading volume exceeds that of the past 38 trading days (MA.38). The only difference between Charting Type 1 and Charting Type 2 is from the last condition about the trading volume. Trading day t to trading day $t+l+d-1$ is the observing period. If the pattern is detected, we will perform the transaction after day $t+l+d-1$.

DATA ANALYSIS

The S&P 500 Equity Indices are world renowned. The characteristics of the S&P 500 Index are that it captures a large-cap segment of the market with at least US$4.0 billion in unadjusted market capitalization; has at least a 50% public float; and has four consecutive quarters of positive earnings and other criteria (http://www.standardandpoors.com/). Our study diagnoses each equity in the S&P 500 Index from January 1977 to December 2010. Return R_i is defined as $R_i = (P_i - P_{i-1})/P_{i-1}$. Exhibit 3 gives the summarized results of the S&P 500 using the proposed techniques. Detailed results are available in Exhibits A1 and A2 in the Appendix.

From Exhibit 3, we can see that the mean return rate reaches a maximum of 4.15% for Charting Type 1 and 2.68% for Charting Type 2, respectively, at day 10, which suggests that we should buy the stock at day 1 after the pattern is completed and sell the stock at day 10 to maximize the profits.

Exhibit 3
Results from Charting Type 1 and Type 2

	R_{day1}	R_{day2}	R_{day3}	R_{day4}	R_{day5}	R_{day10}	R_{day15}	R_{day20}	R_{day25}	R_{day30}
Type 1										
mean*100%	0.42	0.71	0.8	0.51	2.02	4.15	1.67	–0.11	0.55	–0.25
sd*100%	2.92	5.59	7.66	8.22	10.35	10.64	12.13	15.55	18.76	21.13
Type 2										
mean*100%	0.24	0.31	–0.14	–0.1	0.56	2.68	1.61	2.13	1.96	0.93
sd*100%	2.52	5.04	6.67	6.98	9.05	9.49	11.21	12.35	13.29	15.87

*Note: R_{day1} means return rate of day 1 after the cycle, similarly define R_{day2} until R_{day30}; mean*100% is the mean return rate of all the stocks satisfying the pattern; sd*100% is the standard deviation of the return rate.*

CONCLUSIONS

Technical analysis has received considerable attention for many decades. The literature that evaluates the performance of the trading strategies has found mixed results. The purpose of this study is to find a complete data-driven technical analysis algorithm to identify patterns in stock prices and to evaluate the usefulness of trading strategies based on the proposed patterns. We smooth the price data using a local linear regression. Empirical implementation on S&P 500 Index stocks indicates that the proposed technical analysis is very informative and the mean return rate is promising. Future research may check for varying window size in order to identify not only short-term trends but also intermediate and long-term trends.

APPENDIX

EXHIBIT A1

Results from Charting Type 1

Stock	s-date	R_{day1}	R_{day2}	R_{day3}	R_{day4}	R_{day5}	R_{day10}	R_{day15}	R_{day20}	R_{day25}	R_{day30}
A	19991118	0.015	0.0263	0.0733	0.0507	0.0225	0.0273	0.1671	0.1512	0.456	0.6229
A	20060814	0.0119	0.0158	0.0137	0.0085	0.0207	0.0614	0.0766	0.0155	0.0359	0.0228
ADBE	20020308	−0.0566	−0.0653	−0.0965	−0.094	0.0322	0.0481	−0.0793	−0.0895	−0.1226	−0.098
ADP	19951229	−0.024	−0.0268	−0.0419	−0.0388	−0.0719	−0.0628	−0.0419	−0.0388	−0.0568	−0.0419
AIG	20090629	0.017	0.048	0.0517	0.1669	0.4811	0.2926	0.1625	0.2356	0.3808	0.3337
AMZN	20011217	0.0302	0.076	0.0395	0.0085	0.0047	0.1062	0.2659	0.2202	0.124	0.1047
APH	19960628	0.0061	0.0061	−0.0066	0.0127	0.0061	−0.0066	0	0.0891	0.1528	0.1462
BCR	20000302	−0.0269	−0.0183	−0.0169	−0.0239	−0.0422	−0.0169	−0.007	0.0185	0.0296	−0.0381
BIG	20020715	0.0141	0.0445	0.0831	0.1036	0.0907	0.0486	0.0246	−0.185	−0.2073	−0.0521
BTU	20100514	0.0133	7.00E-04	0.0096	0.0108	0.0112	0.0588	0.0482	0.1346	0.0772	0.0705
CEPH	19921202	−0.0741	−0.1481	−0.1111	−0.1111	−0.0741	−0.1667	−0.1852	−0.2037	−0.1667	−0.1852
CHK	20081008	−0.05	−0.06	−0.2107	−0.2453	−0.0613	0.0433	0.0413	0.0433	0.2193	0.0273
CVC	20100514	0.0096	0.0171	0.0478	0.0283	0.041	0.0159	0.0673	0.0932	0.0287	0.0171
DV	19961211	−0.0097	−0.0097	0	0	0.005	0	−0.0924	−0.2039	−0.1359	−0.141
EXPE	20080623	0.0146	0.0021	−0.0136	−0.0376	−0.023	−0.0417	−0.0798	−0.1122	−0.1262	−0.1674
GS	19990802	0.0185	0.0124	0.0236	0.0102	0.0031	0.0391	0.0195	0.0185	0.1863	0.1554
HAR	19920424	0.032	0.0736	0.0736	0.0528	0.0424	−0.0312	−0.0528	−0.0632	−0.0416	−0.1368
HIG	20090326	−0.0242	−0.0416	−0.0665	−0.0808	−0.0851	−0.0752	−0.1479	−0.3039	−0.2784	−0.2561
HPQ	20040810	−0.0031	−0.0073	0.0031	−0.0047	−0.0293	−0.0476	−0.0617	−0.0241	0.0298	0.0115
JWN	20080709	0.0161	0.0717	0.0286	0.0469	0.1106	0.0402	0.0437	−0.1084	−0.2238	−0.3878
LLTC	20000405	0.0162	0.0346	0.1065	0.0764	0.0614	0.1819	0.1237	0.0119	0.1022	0.2023
LSI	20010622	0.0314	−0.0244	−0.0217	−0.0853	−0.0323	−0.0041	−0.1798	−0.4163	−0.4929	−0.4329
MFE	19941115	0.0135	0.0135	0	0.007	0.027	−0.0676	−0.1384	−0.1081	0.0778	0.0946
NBL	20081126	0.0312	0.0714	0.0421	0.0794	0.0529	0.1131	0.1139	4.00E-04	−0.0514	−0.1158
NEE	10081002	−0.0081	0.0021	0.0083	−0.0633	−0.0531	−0.0606	−0.0077	−0.0261	0.0407	0.0567
NTAP	20000406	0.0795	0.153	0.1866	0.1444	0.21	0.1713	0.3563	0.2788	0.2091	0.4647
NVLS	19950412	0	0.0311	0.0407	0.0154	0.0174	0.1067	0.064	0.0679	0.2154	0.1261
PEP	19900913	−0.0248	−0.05	−0.0448	−0.0248	0	0.04	0.04	0.06	0.0352	0.0552
PHM	20010216	0.022	0.0148	0.0112	0.0853	0.0889	0.2644	0.0881	0.187	0.164	0.0769
PRU	20021003	0.016	0.0266	0.0307	0.0444	0.041	0.0816	0.0922	0.0809	0.0894	0.1481
PRU	20090326	−0.0284	−0.0324	−0.056	−0.0563	−0.0808	−0.0343	−0.0782	−0.1483	−0.1347	−0.1132
Q	19990901	−0.0106	−0.0267	0.0575	0.0342	0.0037	0.0612	0.1115	0.081	−0.0178	0.0646
SLM	20081106	0.0191	0.0921	0.2101	0.1843	0.1427	0.2933	0.0955	0.2865	0.1236	−0.0236
SNDK	20020122	−0.0019	0.0063	−0.03	0.013	0.0198	0.1107	−0.0425	−0.0159	−0.0628	−0.2127
TXN	20001121	0.0136	−0.0049	−0.0396	−0.11	−0.1396	−0.1337	−0.2286	−0.2336	−0.3532	−0.3592
UNH	19981014	0.0052	−0.0966	−0.103	−0.0561	−0.103	−0.069	−0.0822	−0.0013	−0.1043	−0.1304
VAR	20040728	−0.002	−0.0403	−0.0313	−0.0179	−0.044	0.1653	0.0801	0.0577	0.0384	0.1253
VLO	19831110	0.0588	0.0818	0.0529	0.0588	0.0699	0.0239	0.0588	0.0239	−0.0298	−0.1287
	mean*100%	0.42	0.71	0.8	0.51	2.02	4.15	1.67	−0.11	0.55	−0.25
	sd*100%	2.92	5.59	7.66	8.22	10.35	10.64	12.13	15.55	18.76	21.13

*Note: s-date means the staring date of the cycle to complete the pattern; R_{day1} means return rate of day 1 after the cycle, similarly define R_{day2} until R_{day30}; mean*100% is the mean return rate of all the stocks satifying the pattern; sd*100% is the standard deviation of the return rate.*

EXHIBIT A2

Results from Charting Type 2

Stock	s-date	R_{day1}	R_{day2}	R_{day3}	R_{day4}	R_{day5}	R_{day10}	R_{day15}	R_{day20}	R_{day25}	R_{day30}
ADBE	20020308	−0.0566	−0.0653	−0.0965	−0.094	0.0322	0.0481	−0.0793	−0.0895	−0.1226	−0.098
AES	20010314	−0.0323	−0.0616	−0.089	−0.0725	−0.0999	−0.0354	−0.0492	−0.1091	−0.1012	−0.1204
AIG	20090629	0.017	0.048	0.0517	0.1669	0.4811	0.2926	0.1625	0.2356	0.3808	0.3337
AMZN	19971030	0.0045	−0.0225	0.027	0.0485	0.0856	−0.0023	0.071	0.0676	0.0631	0.0609
AMZN	20011217	0.0302	0.076	0.0395	0.0085	0.0047	0.1062	0.2659	0.2202	0.124	0.1047
AMZN	20041021	0.0138	−0.0096	−0.0106	−0.0368	−0.026	0.1083	0.0329	0.046	0.0475	0.0462
APC	20081202	0.0208	−0.0169	−0.0432	−0.0602	−0.0234	0.0219	−0.0818	−0.0745	−0.1125	−0.0586
APH	19960628	0.0061	0.0061	−0.0066	0.0127	0.0061	−0.0066	0	0.0891	0.1528	0.1462
APOL	20080326	−0.0261	−0.0283	−0.0606	−0.0582	−0.0702	0.0081	−0.0054	0.0989	0.1633	−0.0525
AXP	19821207	0.0235	0.0058	0.0176	0.0039	0.0293	−0.2039	−0.1548	−0.0803	−0.0921	−0.1137
BCR	20000302	−0.0269	−0.0183	−0.0169	−0.0239	−0.0422	−0.0169	−0.007	0.0185	0.0296	−0.0381
BIG	20020715	0.0141	0.0445	0.0831	0.1036	0.0907	0.0486	0.0246	−0.185	−0.2073	−0.0521
BK	20090720	−0.0185	−0.0065	−0.013	0.0517	0.0524	0.0045	−0.0448	−0.0253	−0.037	0.0014
BTU	20050329	−0.0075	0.0334	0.0285	0.0199	0.0429	0.1276	0.1904	0.2595	0.1572	0.2012
BTU	20100514	0.0133	7.00E−04	0.0096	0.0108	0.0112	0.0588	0.0482	0.1346	0.0772	0.0705
CHK	20081008	−0.05	−0.06	−0.2107	−0.2453	−0.0613	0.0433	0.0413	0.0433	0.2193	0.0273
CMCSA	20070209	0.0095	0.0038	0.0133	0.0402	0.0573	0.0455	0.0281	0.0334	−0.0137	0.0205
CMI	20090729	0.019	0.0045	−0.0192	−0.0154	−0.006	−0.0161	0.0652	0.1283	0.0806	−0.0156
COST	19930412	−0.0085	0	−0.0129	−0.0085	−0.0169	0.2542	0.178	0.1441	0.14	0.1356
CTSH	20030331	0	0.0195	0.0088	0.0176	0.0127	0.122	0.1835	0.1586	0.2196	0.3324
CTSH	20030401	0.0195	0.0088	0.0176	0.0127	−0.0342	0.122	0.2079	0.1201	0.1903	0.366
CVC	20100514	0.0096	0.0171	0.0478	0.0283	0.041	0.0159	0.0673	0.0932	0.0287	0.0171
DGX	20010105	0.0032	−0.0204	−0.0461	−0.0329	−0.0754	−0.1681	−0.2226	−0.1332	−0.1063	−0.0735
DNB	20000921	0.0169	0.0626	0.1143	0.1143	0.0599	0.0654	0.1312	0.1399	0.1284	0.1709
ETR	20010919	−0.0146	−0.01	−0.0288	−0.0316	−0.0188	−0.0519	−0.0416	−0.0113	−0.0493	−0.0213
EXPE	20080623	0.0146	0.0021	−0.0136	−0.0376	−0.023	−0.0417	−0.0798	−0.1122	−0.1262	−0.1674
FAST	19950329	0.0084	−0.0084	−0.0168	−0.0588	−0.0588	−0.1513	−0.1388	−0.0548	−0.04	−0.0588
FMC	20081126	0.0075	0.0066	0.0115	0.0377	0.0185	0.0415	0.0728	−0.0351	−0.1077	−0.207
GAS	20020717	−0.0404	−0.0171	−0.0514	−0.0229	−0.0021	−0.0538	−0.0342	−0.1123	−0.0291	0.0236
GS	19990802	0.0185	0.0124	0.0236	0.0102	0.0031	0.0391	0.0195	0.0185	0.1863	0.1554
HIG	200903267	−0.0242	−0.0416	−0.0665	−0.0808	−0.0851	−0.0752	−0.1479	−0.3039	−0.2784	−0.2561
HPQ	20040810	−0.0031	−0.0073	0.0031	−0.0047	−0.0293	−0.0476	−0.0617	−0.0241	0.0298	0.0115
HRB	19911001	0.0035	−0.0433	−0.0038	−0.0182	−0.0072	−0.0144	0.0289	0.0072	0.0866	0.0973
JBL	19960126	−0.023	−0.0689	−0.0809	−0.1039	−0.1608	−0.0809	−0.1728	−0.0809	−0.0809	0.0588
JDSU	20060905	−0.0174	−0.0188	−0.0255	−0.0584	−0.0423	0.0912	0.1636	0.283	0.2106	0.1918
JWN	20080709	0.0161	0.0717	0.0286	0.0469	0.1106	0.0402	0.0437	−0.1084	−0.2238	−0.3878
KEY1	20080707	0.04	0.0666	0.119	0.1288	0.0586	0.1368	0.1714	0.2433	0.1732	−0.4298
LEG	19920608	−0.0055	−0.0105	−0.0105	−0.0316	−0.0371	−0.0265	−0.0371	−0.0055	0.0632	−0.016
LH	20020927	0.029	0.0177	−0.0017	−0.0104	−0.013	0.0432	0.0393	−0.0061	4.00E−04	0.032
LLTC	20000405	0.0162	0.0346	0.1065	0.0764	0.0614	0.1819	0.1237	0.0119	0.1022	0.2023
MSI	19991230	0.0218	−0.0093	−0.014	0.07	0.0584	0.0541	−0.0614	0.0198	−0.0358	−0.0855
NBL	20081006	−0.019	−0.1663	−0.1304	−0.1145	−0.2259	−0.04	−0.1406	−0.1364	0.0107	−0.1156
NEE	20081002	−0.0081	0.0021	0.0083	−0.0633	−0.0531	−0.0606	−0.0077	0.0261	0.0407	0.0567
NKE	19901004	−0.0106	0.0106	−0.042	−0.014	0.0034	0.0072	0.0778	0.1304	0.0741	0.0567
NTAP	20000406	0.0795	0.153	0.1866	0.1444	0.21	0.1713	0.3563	0.2788	0.2091	0.4647
NVLS	19910220	0.0625	0.1146	0.0521	−0.0104	−0.0262	0	−0.0938	−0.0417	−0.1562	−0.0521
NVLS	19950412	0	0.0311	0.0407	0.0154	0.0174	0.1067	0.064	0.0679	0.2154	0.1261
PEP	19900913	−0.0248	−0.05	−0.0448	−0.0248	0	0.04	0.04	0.06	0.0352	0.0552
PHM	20040102	0.0508	0.0988	0.0765	0.0695	0.0948	0.0854	0.096	0.0874	0.1054	0.0078
PRU	20021003	0.016	0.0266	0.0307	0.0444	0.041	0.0816	0.0922	0.0809	0.0894	0.1481
RAI	20101110	3.00E−04	0.0308	0.011	0.0119	−0.0024	−0.0241	−0.0137	−0.0128	−0.025	0.0268
RHI	20100601	0.0131	0.0038	−0.0154	−0.0327	−0.0323	−0.0269	−0.0884	−0.123	−0.141	−0.0765
SCHW	19900914	−0.0284	−0.0374	−0.0471	−0.0374	−0.0374	−0.0374	−0.0561	−0.1121	−0.0471	−0.0658
SCHW	20000601	−0.0233	−0.0217	−0.0887	−0.0316	0.0169	0.0268	0.0118	0.0153	0.0118	0.0421

EXHIBIT A2 *(Continued)*

Stock	s-date	R_{day1}	R_{day2}	R_{day3}	R_{day4}	R_{day5}	R_{day10}	R_{day15}	R_{day20}	R_{day25}	R_{day30}
SLM	20030609	–0.0123	–0.006	–0.0174	–0.0224	–0.0031	–0.0104	–0.0174	–0.0275	–0.0342	–0.0863
SLM	20081106	0.0191	0.0921	0.2101	0.1843	0.1427	0.2933	0.0955	0.2865	0.1236	–0.0236
TROW	19950911	–0.0192	0.0239	0.0287	0.0263	0.0382	0.0287	0.0049	0.0119	0.0431	0.0443
TROW	19970326	–0.0204	0.0206	0.0028	0.0155	0.0015	0.0155	–0.0051	0.0206	0.0285	0.0669
TXN	20001121	0.0136	–0.0049	–0.0396	–0.11	–0.1396	–0.1337	–0.2286	–0.2336	–0.3532	–0.3592
UNH	19981014	0.0052	–0.0966	–0.103	–0.0561	–0.103	–0.069	–0.0822	0.0013	–0.1043	–0.1304
UNM	19970530	–0.0101	–0.0425	–0.0517	–0.0543	–0.0517	–0.0647	–0.1114	–0.1114	–0.1256	–0.1075
VAR	20040728	–0.002	–0.0403	–0.0313	–0.0179	–0.044	0.1653	0.0801	0.0577	0.0384	0.1253
VLO	19831110	0.0588	0.0818	0.0529	0.0588	0.0699	0.0239	0.0588	0.0239	–0.0298	–0.1287
VTR	19990415	0.0112	0.0446	0.0576	0.0688	0.0688	0.0446	–0.0483	–0.0929	–0.0818	–0.0483
WFC	19890720	–0.0054	–0.0054	–0.0054	0.0058	0	0.0112	0.0559	0.0671	0.0224	–0.0165
XOM	19871123	–0.0213	–0.0552	–0.0491	–0.0275	0	0.0061	–0.0184	0.0184	0.0523	0.0461
	mean*100%	0.24	0.31	–0.14	–0.1	0.56	2.68	1.61	2.13	1.96	0.93
	sd*100%	2.52	5.04	6.67	6.98	9.05	9.49	11.21	12.35	13.29	15.87

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