# Technical Analysis: Neural Network Based Pattern Recognition of Technical Trading Indicators, Statistical Evaluation of their Predictive Value, and a Historical Overview of the Field



by

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B.S., Applied Mathematics and Electrical Engineering
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Submitted to the Department of Electrical Engineering and Computer Science
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## Abstract

We revisit the kernel regression based pattern recognition algorithm designed by Lo, Mamaysky, and Wang (2000) to extract nonlinear patterns from the noisy price data, and develop an analogous neural network based one. We argue that, given the natural flexibility of neural network models and the extent of parallel processing that they allow, our algorithm is a step forward in the automation of technical analysis. More importantly, following the approach proposed by Lo, Mamaysky, and Wang, we apply our neural network based model to examine empirically the ability of the patterns under consideration to add value to the investment process. We discover overwhelming support for the validity of these indicators, just like Lo, Mamaysky, and Wang do. Moreover, this basic conclusion appears to remain valid across different levels of smoothing and insensitive to the nuances of pattern definitions present in the technical analysis literature. This confirms that Lo, Mamaysky, and Wang's results are not an artifact of their kernel regression model, and suggests that the kinds of nonlinearities that technical indicators are designed to capture constitute some underlying properties of the financial time series itself. Finally, we complement our empirical analysis with a historical one, focusing on the origins of trading and speculation in general, and technical analysis in particular.

Thesis Supervisor: Andrew W. Lo
Title: Harris and Harris Group Professor, Sloan School of Management

# Acknowledgments

I would like to express my sincere gratitude to my advisor, Professor Andrew Lo, whose thoughtful guidance, advice, understanding, and encouragement have made every aspect of this project, as well as my graduate education as a whole, truly rewarding and enjoyable. I am grateful to Professor Munther Dahleh, Mike Epstein, Mila Getmansky, Marilyn Pierce, Dmitry Repin, and Svetlana Sussman for their invaluable and ever-present support and counsel. I thank all my LFE colleagues, past and present, for a stimulating and supportive environment. I remain forever indebted to my undergraduate advisor, Professor Narendra, for providing me with the right foundation at the critical juncture of my education. I also thank my friends, roommates, classmates, instructors, and everyone else who either directly or indirectly has contributed to my success. My gratitude to my family goes beyond the words.

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# Chapter 1

# Introduction

The idea that stock market prices follow a random walk was first anticipated more than a century ago by a French graduate student Louis Bachelier (1870 - 1946) in his 1900 doctoral dissertation, *Théorie de la Spéculation.*[1] Unfortunately, the dissertation, now deemed the "origin of mathematical finance," fell into oblivion [16, p. 344]. Fifty-three years later, a British statistician by the name of Maurice G. Kendall presented a paper, *The Analysis of Economic Time-Series - Part I: Prices*, to the Royal Statistical Society, in which he insisted that "there [was] no hope of being able to predict movements on the exchange for a week ahead without extraneous information" [33, p. 11]. Rather, it was "almost as if once a week the Demon of Chance drew a random number from a symmetrical population of fixed dispersion and added it to the current price to determine the next week's price" [33, p. 13]. It is from this rediscovery that the Random Walk Hypothesis stems [6, p. 354].

[1]See Bachelier, L. *Théorie de la Spéculation.* Gauthiers-Villars, Paris: 1900. Translated into English by A.J. Boness in Cootner, P.H. (ed.). *Random Character of Stock Market Prices.* MIT Press, Cambridge: 1964.

A great deal of research has been devoted to testing empirically the Random Walk Hypothesis ever since, and much of it turned out in its favor, especially early on. For example, in their important study, Fama and Blume (1966) investigate whether the degree of dependence between successive price changes of individual securities can make expected profits from following a mechanical trading rule known as Alexander's filter technique greater than those of a buy-and-hold strategy. They conclude that the market is indeed efficient and that, even from an investor's viewpoint, the random-walk model is an adequate description of the price behavior. Such conclusion rules out the possibility that technical analysts, also known as chartists, whose principal assumption is that past prices contain information for predicting future returns, can add value to the investment process. Consequently, technical analysis has been largely discredited in the academic world, with Burton G. Malkiel, the author of the influential *A Random Walk Down Wall Street* (1996), concluding that "under scientific scrutiny, chart-reading must share a pedestal with alchemy."

Though to this day many academics remain critical of the discipline, an increasing number of studies suggests, either directly or indirectly, that "technical analysis may well be an effective means for extracting useful information from market prices" [37, p. 1705]. For example, Granger and Morgenstern (1963) suggest that the random walk model ignores the possibly important low-frequency (long-run) components of the time series of stock market prices. Treynor and Ferguson (1983) show that it is not only the past prices, but the past prices plus some valuable nonpublic information, that can lead to profit. Lo and MacKinlay (1988) strongly reject the Random Walk Hypothesis for weekly stock market returns by using a simple volatility-based specification test. Pruitt and White (1988) test the performance of a multi-component technical trading system, and conclude that it does better that a simple buy-and-hold strategy to an extent that could not be attributed to chance alone. Brock, Lakonishok, and LeBaron (1992) find that the moving average and the trading range break technical indicators do posses some predictive power, and that the returns that they generate are unlikely to be generated by the four popular null models (a random walk with drift, AR(1), GARCH-M, and EGARCH). Chang and Osler (1994) suggest that the head-and-shoulders pattern has some predictive power in foreign exchange markets. Using genetic programming to investigate whether optimal trading rules can be revealed by the data themselves, Neely, Weller, and Dittmar (1997) discover strong evidence of economically significant out-of-sample excess returns after the adjustment for transaction costs for the exchange rates under consideration. Brown and Goetzmann (1998) reevaluate Alfred Cowles' (1934) test of the Dow Theory (as interpreted by Hamilton),[2] and conclude that the Hamilton strategy can reduce portfolio volatility and yield profits that are higher than those of the buy-and-hold. Allen and Karjalainen (1999) use genetic programming to discover optimal trading rules for the S&P 500 index, and find that their rules do exhibit some forecasting power. Lo, Mamaysky, and Wang (2000) find that certain technical patterns, when applied to many stocks over many time periods, do provide incremental information, especially for Nasdaq stocks; it is their work that becomes the focal point of this thesis.

[2]Cowles' (1934) test provided "strong evidence" against the ability of the Dow Theory to forecast stock market prices.

# Chapter 2

# Neural Network Based Pattern Recognition of Technical Trading Indicators and Statistical Evaluation of their Predictive Value

## 2.1 Objectives and Outline

In their 2000 paper, *Foundations of Technical Analysis*, Lo, Mamaysky, and Wang propose a novel kernel regression based pattern recognition algorithm which extracts nonlinear patterns from the noisy price data. Developing such an algorithm is in itself useful, as it is a step towards the automation of technical analysis. In this thesis, we propose an analogous neural network based pattern recognition algorithm, which, in the light on the natural flexibility of neural network models and given the extent of parallel processing that they allow, constitutes a, however modest, step forward in the automation of technical analysis. We then apply our neural network based model in the same way Lo, Mamaysky, and Wang apply their kernel regression based one, that is, to investigate the ability of technical trading patterns to forecast future price moves. This allows us to examine whether Lo, Mamaysky, and Wang's results are the consequence of the efficacy of technical analysis, rather than an artifact of their kernel regression model. In other words, if the conclusions of the said authors are due to the ability of technical indicators to capture some underlying properties of the financial time series, then our conclusions should match theirs.

## 2.2 Automating Technical Analysis: A Pattern Recognition Algorithm

Our pattern recognition algorithm consists of three parts:

1. Constructing a neural network model of a given time series of prices,

2. Defining technical patterns quantitatively, in terms of their geometric properties, and

3. Scanning the neural network model for the presence of technical patterns.

Each of these parts will be dealt with in turn in the following sections.

### 2.2.1 A neural network model

As Lo, Mamaysky, and Wang point out, at the heart of technical analysis is the recognition that prices evolve in a nonlinear fashion over time, and that this evolution contains certain regularities or patterns. More precisely, we can say that a time series of prices is a sum of a nonlinear pattern and white noise, namely

$$P_t = m(X_t) + \varepsilon_t, \;\; t = 1, 2, ..., T \tag{2.1}$$

where $m(X_t)$ is an arbitrary fixed but unknown nonlinear function of a state variable $X_t$ and $\{\varepsilon_t\}$ is white noise. [37, p. 1708]

However, before we can examine the significance of the information content of technical patterns, we must be able to identify, or extract, these patterns from the nonlinear time series of prices. Here it is important to realize that identifying patterns from the raw price data directly would not be sensible. As Lo, Mamaysky, and Wang put it, such approach "identifies too many extrema and also yields patterns that are not visually consistent with the kind of patterns that technical analysts find compelling" [37, p. 1720]. When professional technicians study a price chart, their eyes naturally smooth the data, while their cognition discerns regularities. Moreover, many would argue that much of this process takes place on an intuitive and subconcious level, making it even harder to quantify.

Logical first candidates for modeling a process by which technicians look for patterns in a price chart are smoothing estimators, since, as Lo, Mamaysky, and Wang explain, "smoothing estimators are motivated by their close correspondence to the way human cognition extracts regularities from noisy data" [37, p. 1709]. In this regard a neural network seems to be particularly suitable, since the motivation for it comes directly from the human brain. Just like the brain is a network formed by interconnections of biological neurons, an artificial neural net is formed by interconnections of artificial neurons. The structure of an artificial neuron is similar to that of its biological counterpart. A biological neuron accepts different input signals through dendrites, combines them in its body, or soma, and outputs them through the axon. Similarly, an artificial neuron accepts different input signals, weights them, sums them, and outputs the resulting signal through a transformation $\gamma$. When we say that an artificial neural network "learns," we mean that its weights undergo training and adaptation. The weights themselves constitute the memory of the system, and determine the behavior of the network. They can be trained by various algorithms to approximate functions and lead to "intelligent" behavior. [43]

More formally, suppose that there exists a set of inputs that belong to a set $U \subset \mathcal{R}^p$ and a corresponding set of outputs that belong to a set $V \subset \mathcal{R}^m$, and let $f : \mathcal{R}^p \to \mathcal{R}^m$ be a mapping between an input space and an output space. Our task is to use input and output data to approximate this mapping. In particular, let $f : \mathcal{R}^p \to \mathcal{R}^m$, an unknown function to be approximated, be defined by a finite set of input-output pairs $\{u^{(i)}, v^{(i)}\}$, so that $f[u^{(i)}] = v^{(i)}$. Let $F(\theta) : \mathcal{R}^p \to \mathcal{R}^m$ be a parameterized function corresponding to a neural network, where $\theta = [\theta_1, \theta_2, ..., \theta_N]^T$ is a parameter vector of dimension N. Our task is to determine $\theta^*$ based on the available data in such a way that would make $F(\theta^*)$ the "best" possible approximation to $f$. [43] One way to accomplish this is to choose $\theta$ such that the sum of squared errors between the target and the network output is minimized. This method of estimating the parameters is known as nonlinear least squares, and is preffered to other methods, such as backpropagation, due to its many practical advantages.[1]

Recall that in the particular case of our problem we have $P_t = m(X_t) + \varepsilon_t$, $t = 1, ..., T$, where $m : \mathcal{R} \to \mathcal{R}$, and where $\{X_j\}$ is the input sequence and $\{P_j\}$ is the target sequence. The input sequence $\{X_j\}$ is chosen to be the time with increments of 0.1, namely $\{X_j\} = \{1, 1.1, 1.2, ..., T\}$. Our objective is to approximate $m$ by a neural network model $\hat{m}$. We choose a simple model, a neural network with one hidden layer (also known as a multilayer percepteron with one hidden layer), which, despite its simplicity, posseses the universal approximation property,[2] and is capable of capturing a variety of nonlinearities [35, p. 30]. In particular, we let

$$\hat{m}(X_t; \theta) = \Theta[v_0 + \sum_{i=1}^{n} v_i \Gamma(w_{i0} + w_{i1} X_t)] \tag{2.2}$$

be a neural network representation, where there are only two inputs, $X_t$ and 1, where $\Gamma(\cdot) = \text{htan}(\cdot)$ is the nonliear activation function that is associated with the nodes in the hidden layer, where the activation function $\Theta(\cdot)$ for the output layer is assumed to be the identity function, and where $v_0, ..., v_n, w_{10}, ..., w_{n0}, w_{11}, ..., w_{n1}$ are the $3n+1$ parameters that

[1] See [10], [68].
[2] See [68].

need to be adjusted so that $\hat{m}$ is a good approximation to $m$.

We then let

$$\theta^T = [v_0, ..., v_n, w_{10}, ..., w_{n0}, w_{11}, ..., w_{n1}] \tag{2.3}$$

be the parameter vector, and solve

$$\min_\theta \sum_{\tau=1}^{t} [P_t - \hat{m}(X_\tau; \theta)]^2 \tag{2.4}$$

using nonlinear least squares. Specifically, we use the *lmtrain* Matlab function, which uses the Levenberg-Marquardt algorithm to solve the above-stated nonlinear optimization problem.

**Selecting the number of nodes** Recall that one of our main objectives in using a neural network model is to be able to replicate, at least in part, the kind of smoothing that professional technical analysts are doing with their eyes and their cognition when they look at the price chart. Central to our success in this matter is the selection of an appropriate number of nodes in the hidden layer, since it is the number of nodes that determines the level of smoothing, through an inverse relationship. Following Professor Lo's advice, we base our model selection on the interviews with three professional technical analysts.[3] These techni-

[3]We thank Mike Epstein, Peter Gallagher, and Richard Gula.

cians were presented with a slide show of charts depicting neural network approximations on top of the raw price data, where each chart contained the same raw data but where the number of nodes in the hidden layer of a neural network was increasing progressively. When the said technicians were asked to choose the models that they considered the "best" for the purpose at hand, they opted for those characterized by a relatively low degree of smoothing, with the number of nodes ranging from 18 to 35 across stocks.[4] Note that, while using such a large number of nodes in an economic forecasting application would be unreasonable, it is entirely sensible in the context of our pattern recognition problem.[5] Finally, the robustness of the results is investigated by implementing neural network models characterized by a higher degree of smoothing, with the number of nodes ranging from 7 to 18 across stocks. Please see Figures 1-20 for illustration.

[4]When the numbers that they chose did not coincide, the median number of nodes was implemented.
[5]This conclusion follows from my discussion with Professor Lo.

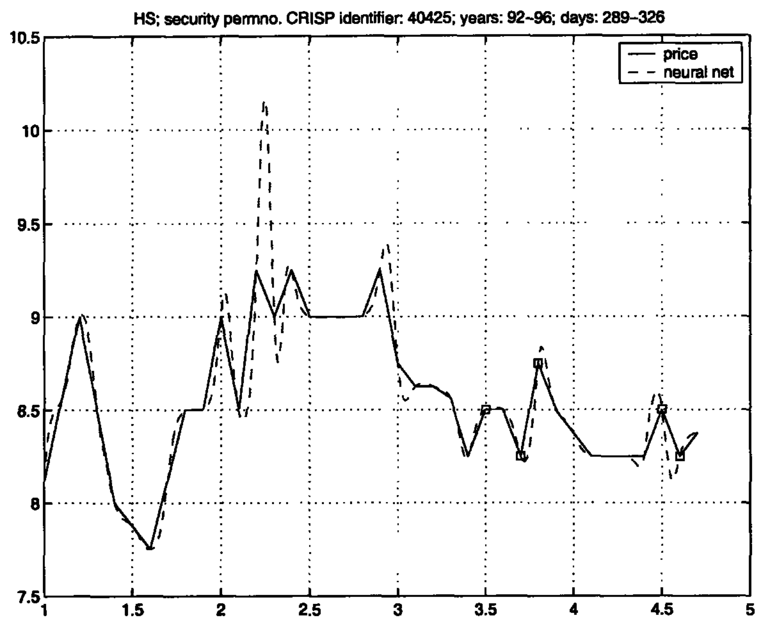


Figure 2-1: Lower Degree of Smoothing Case: Head-and-Shoulders Example

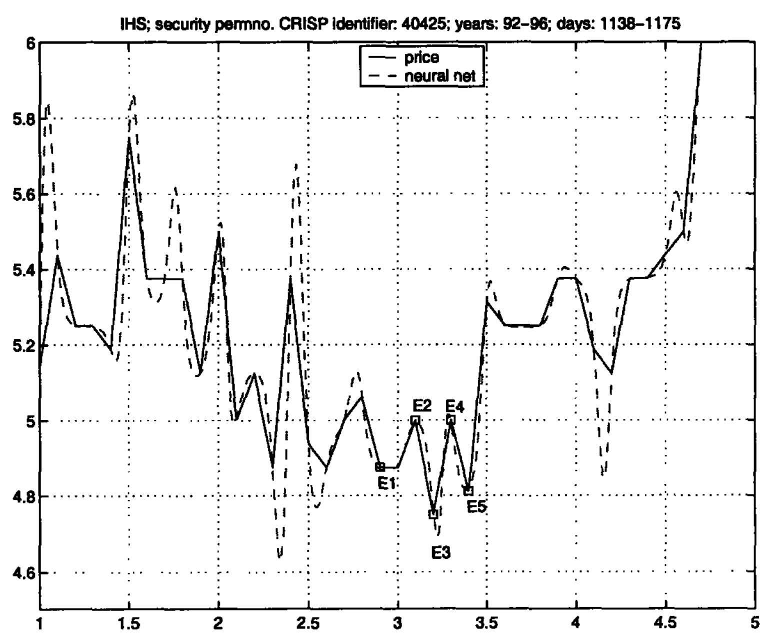


Figure 2-2: Lower Degree of Smoothing Case: Inverse Head-and-Shoulders Example

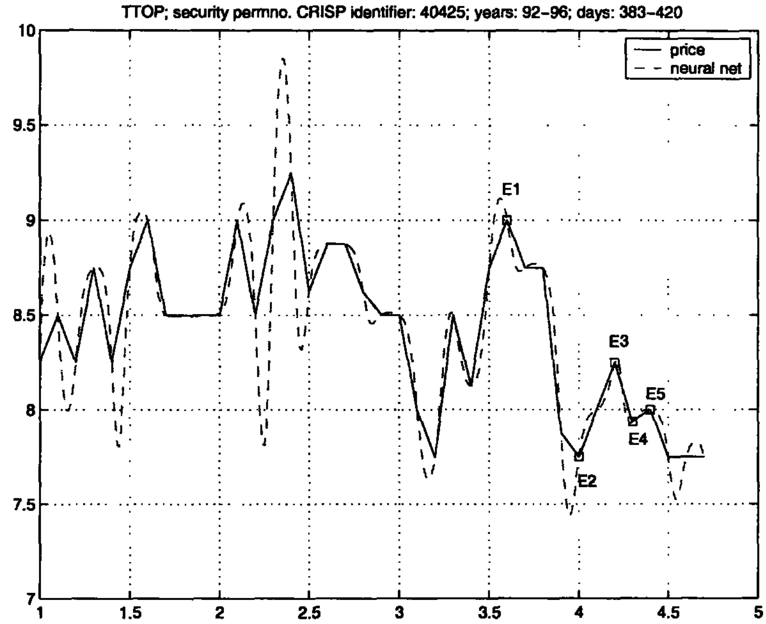


Figure 2-3: Lower Degree of Smoothing Case: Triangle Top Example

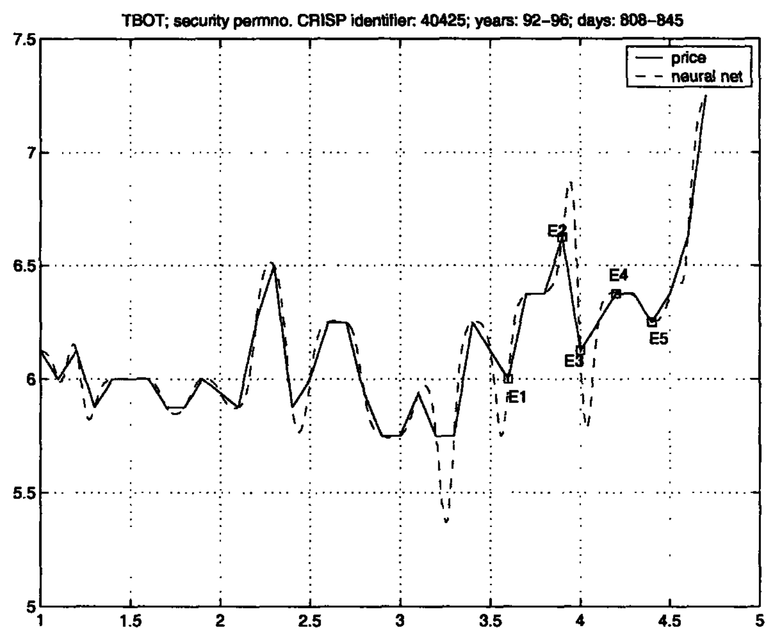


Figure 2-4: Lower Degree of Smoothing Case: Triangle Bottom Example

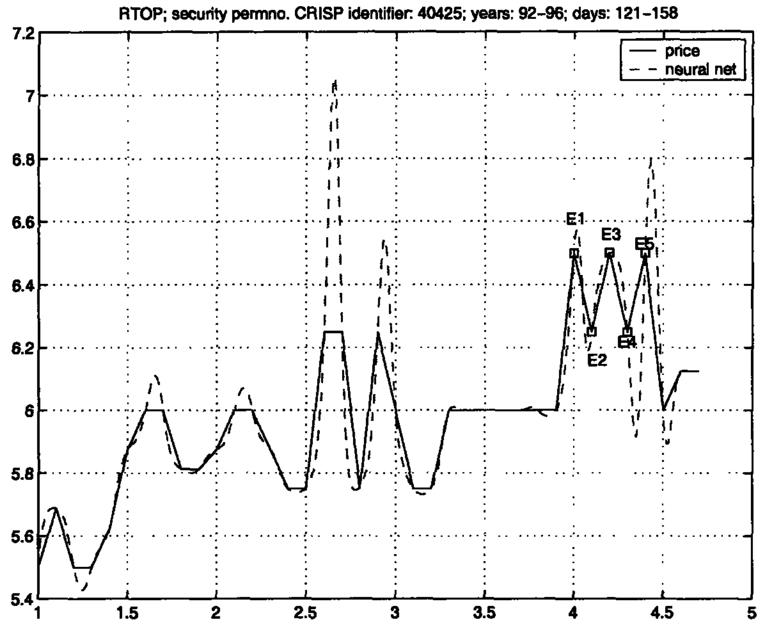


Figure 2-5: Lower Degree of Smoothing Case: Rectangle Top Example

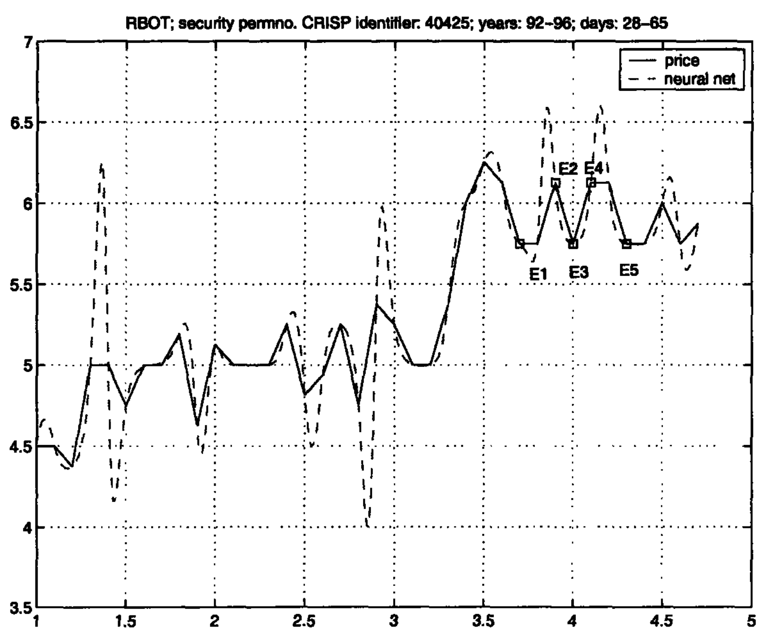


Figure 2-6: Lower Degree of Smoothing Case: Rectangle Bottom Example

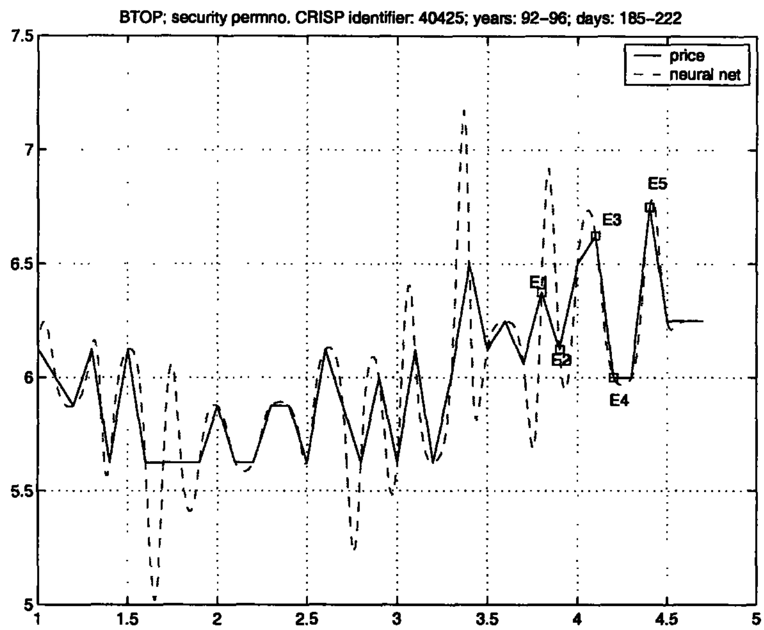


Figure 2-7: Lower Degree of Smoothing Case: Broadening Top Example

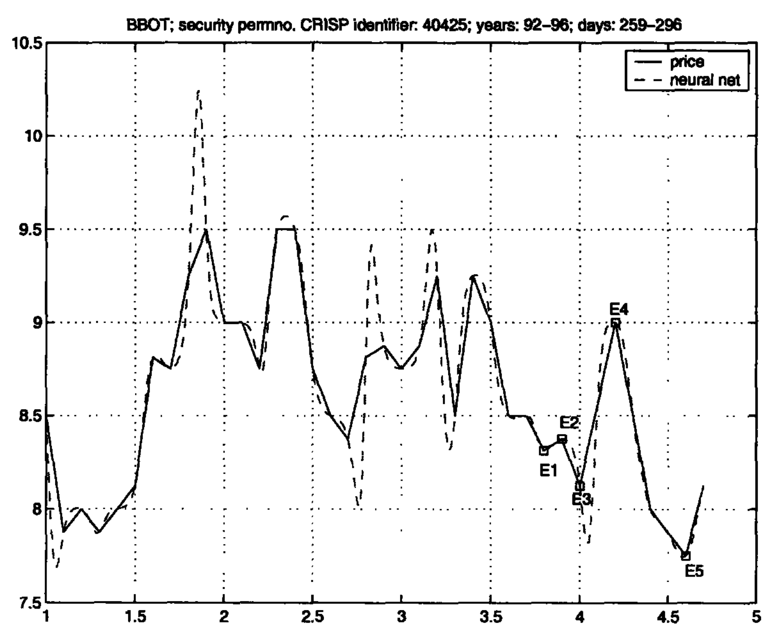


Figure 2-8: Lower Degree of Smoothing Case: Broadening Bottom Example

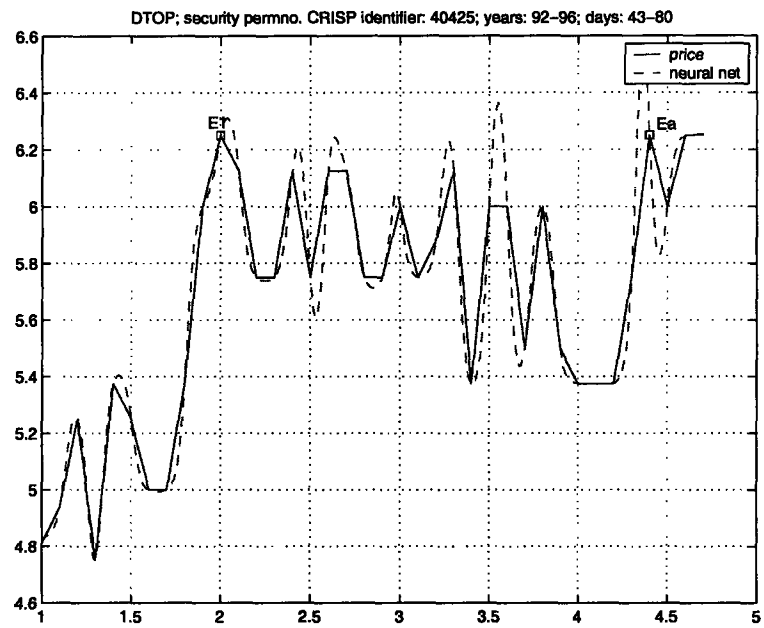


Figure 2-9: Lower Degree of Smoothing Case: Double Top Example

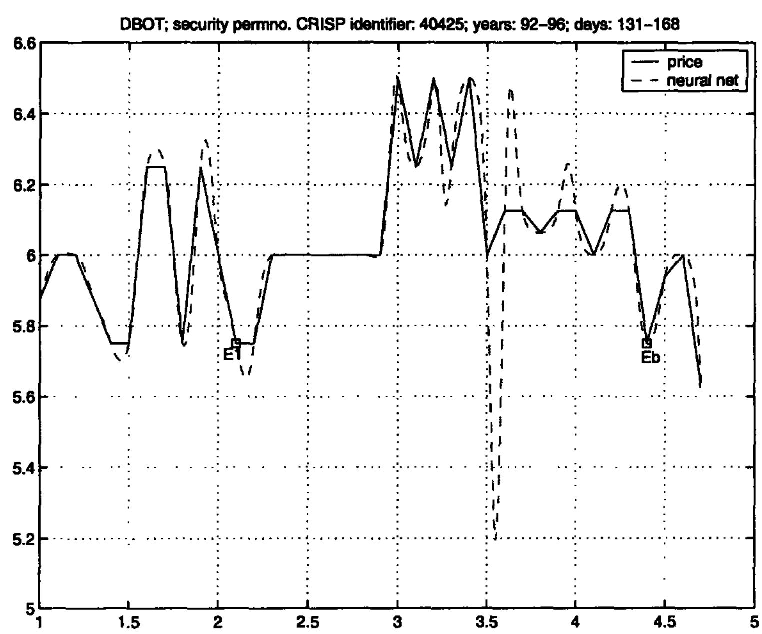


Figure 2-10: Lower Degree of Smoothing Case: Double Bottom Example

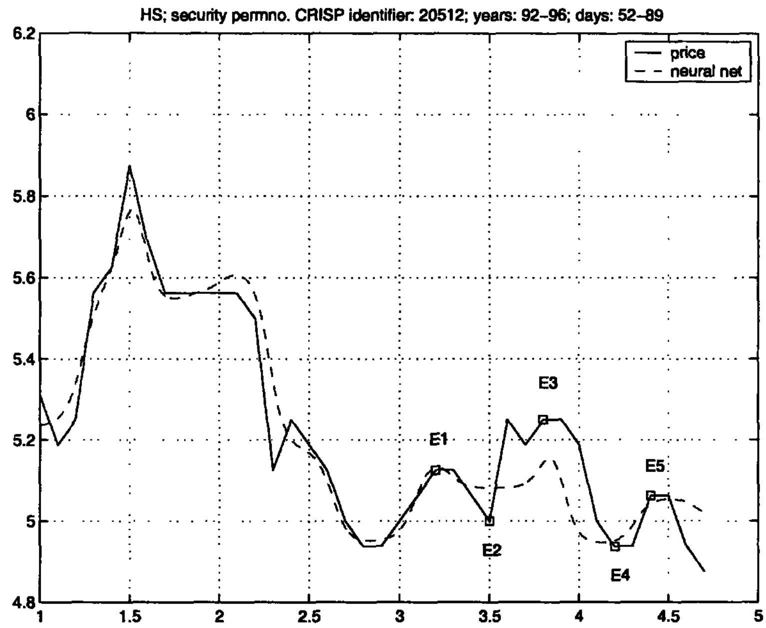


Figure 2-11: Higher Degree of Smoothing Case: Head-and-Shoulders Example

### 2.2.2 Defining technical patterns quantitatively

Before the scanning of the above-described neural network models for the presence of technical patterns can be automated, pattern definitions, presented in non-mathematical language in the technical analysis literature, must be quantified. Following Lo, Mamaysky, and Wang, we consider the ten most commonly used patterns:[6] head-and-shoulders (HS) and inverse head-and-shoulders (IHS), triangle top (TTOP) and bottom (TBOT), rectangle top (RTOP) and bottom (RBOT), broadening top (BTOP) and bottom (BBOT), and double top (DTOP) and bottom (DBOT). We start by summarizing the quantitative versions of the pattern definitions provided by Lo, Mamaysky, and Wang,[7] then proceed to augment these definitions

[6]See, e.g., [42] or [22].
[7]Please see [37, pp. 1716-1718].

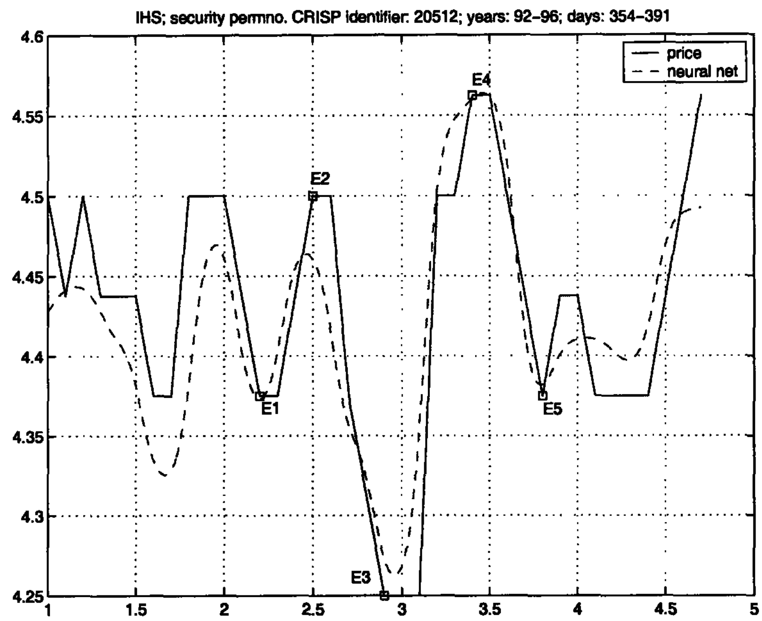


Figure 2-12: Higher Degree of Smoothing Case: Inverse Head-and-Shoulders Example

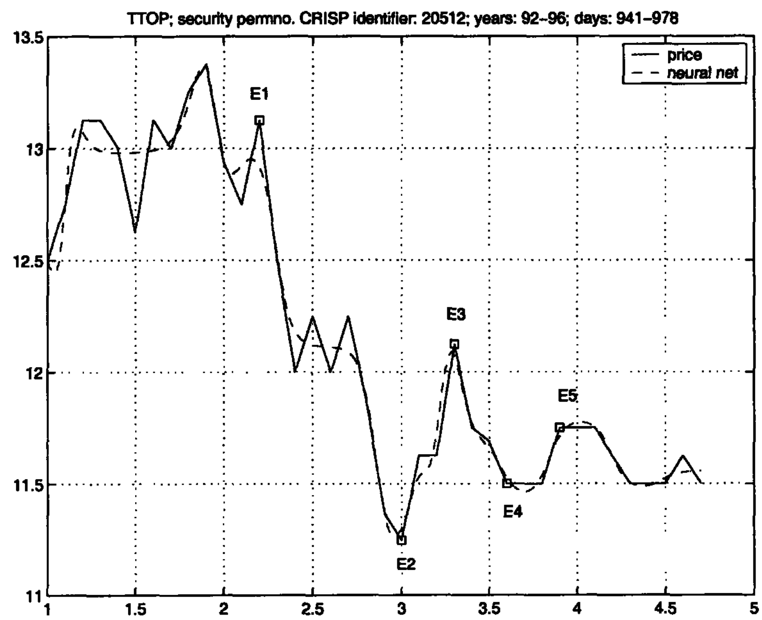


Figure 2-13: Higher Degree of Smoothing Case: Triangle Top Example

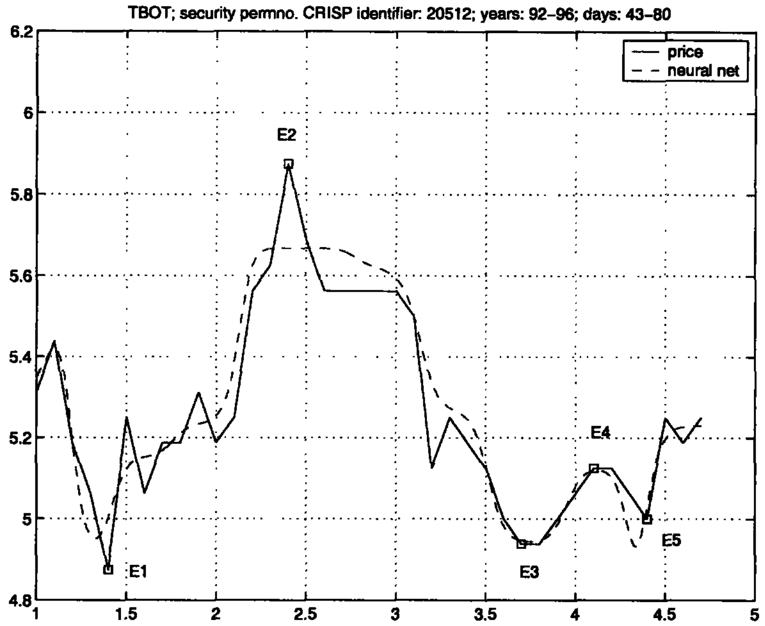


Figure 2-14: Higher Degree of Smoothing Case: Triangle Bottom Example

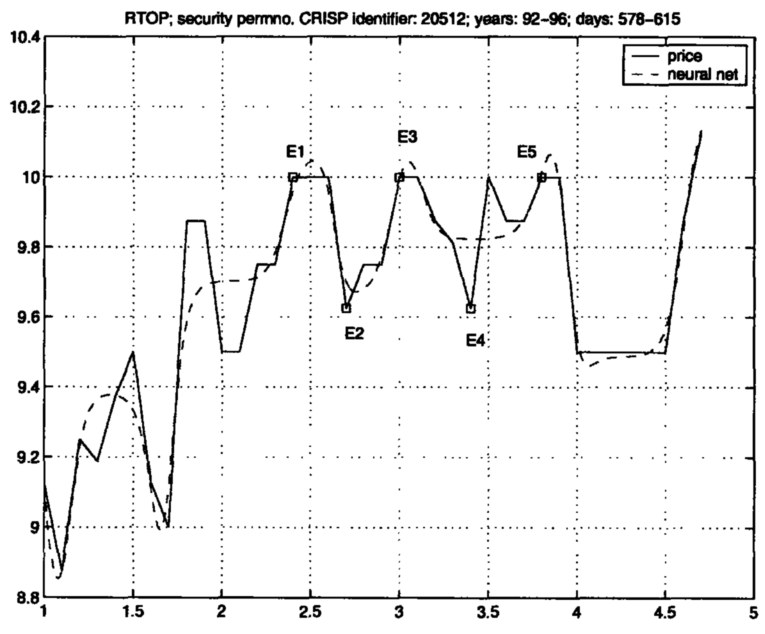


Figure 2-15: Higher Degree of Smoothing Case: Rectangle Top Example

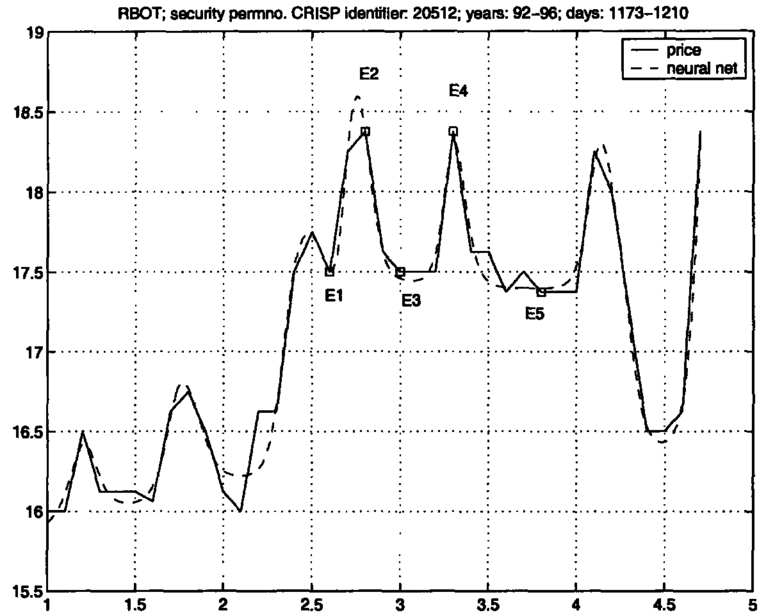


Figure 2-16: Higher Degree of Smoothing Case: Rectangle Bottom Example

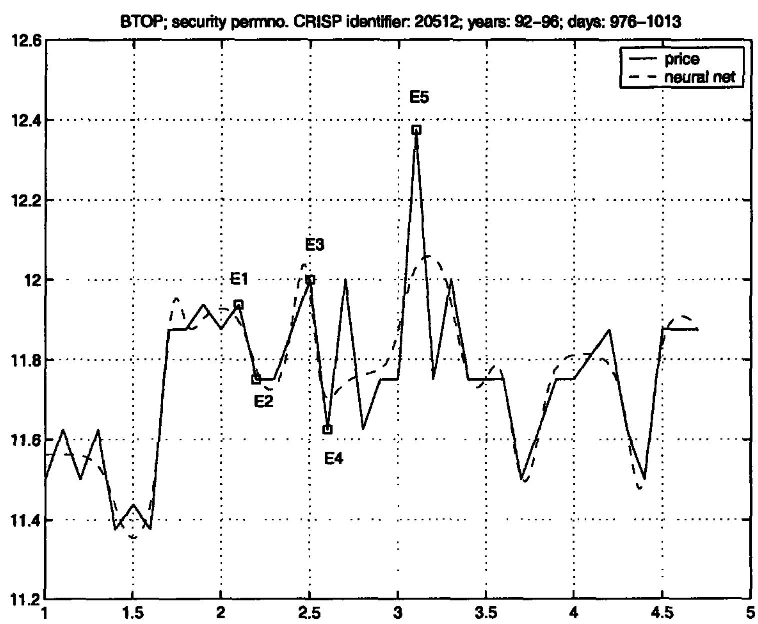


Figure 2-17: Higher Degree of Smoothing Case: Broadening Top Example

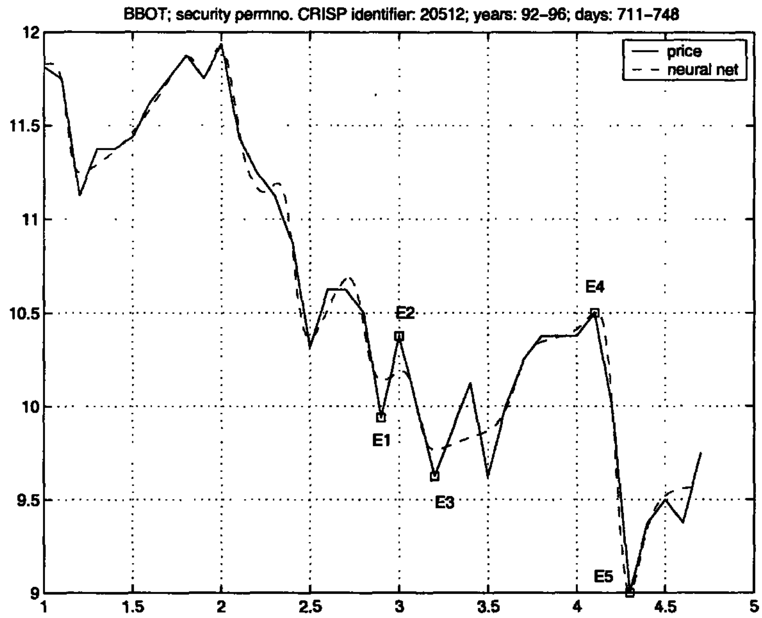


Figure 2-18: Higher Degree of Smoothing Case: Broadening Bottom Example

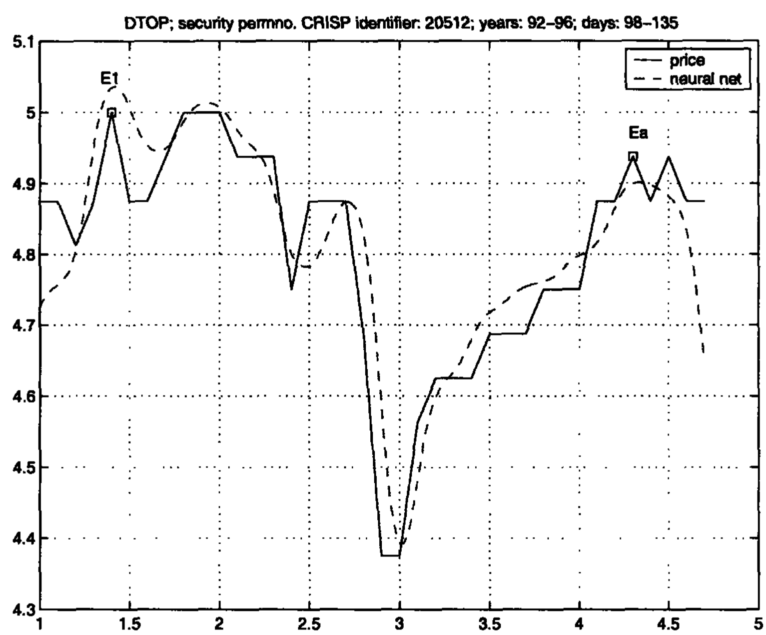


Figure 2-19: Higher Degree of Smoothing Case: Double Top Example

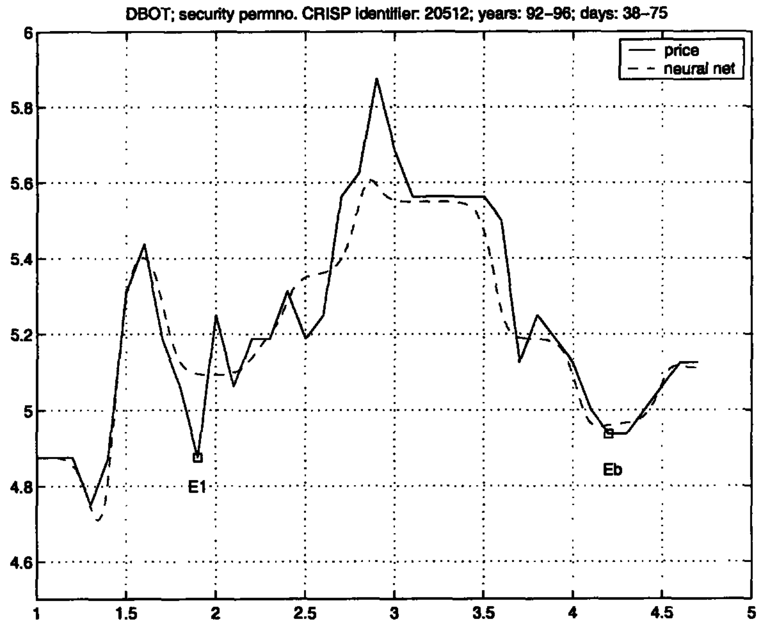


Figure 2-20: Higher Degree of Smoothing Case: Double Bottom Example

by introducing the concept of a neckline.

**Head-and-Shoulders** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a maximum
- $E_3 > E_1$, $E_3 > E_5$
- $E_1$ and $E_5$ are within 1.5 percent of their average
- $E_2$ and $E_4$ are within 1.5 percent of their average

**Inverse Head-and-Shoulders** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a minimum
- $E_3 < E_1$, $E_3 < E_5$
- $E_1$ and $E_5$ are within 1.5 percent of their average
- $E_2$ and $E_4$ are within 1.5 percent of their average

**Triangle Top** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a maximum
- $E_1 > E_3 > E_5$
- $E_2 < E_4$

**Triangle Bottom** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a minimum
- $E_1 < E_3 < E_5$
- $E_2 > E_4$

**Rectangle Top** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a maximum
- tops are within 0.75 percent of their average
- bottoms are within 0.75 percent of their average
- lowest top > highest bottom

**Rectangle Bottom** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a minimum
- tops are within 0.75 percent of their average
- bottoms are within 0.75 percent of their average
- lowest top > highest bottom

**Broadening Top** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a maximum
- $E_1 < E_3 < E_5$
- $E_2 > E_4$

**Broadening Bottom** is defined by a sequence of five consecutive local extrema $E_1, ..., E_5$, such that

- $E_1$ is a minimum
- $E_1 > E_3 > E_5$
- $E_2 < E_4$

**Double Top** is defined by an initial local extremum $E_1$ and a subsequent local extremum $E_a$ such that $E_a \equiv \sup\{P^*_{t_k} : t^*_k > t^*_1,\ k = 2, ..., n\}$, and where

- $E_1$ is a maximum
- $E_1$ and $E_a$ are within 1.5 percent of their average
- $t^*_a - t^*_1 > 22$

**Double Bottom** is defined by an initial local extremum $E_1$ and a subsequent local extremum $E_b$ such that $E_b \equiv \inf\{P^*_{t_k} : t^*_k > t^*_1,\ k = 2, ..., n\}$, and where

- $E_1$ is a minumum

- $E_1$ and $E_b$ are within 1.5 percent of their average

- $t_b^* - t_1^* > 22$

Note that the corresponding top and bottom (or inverse) patterns are mirror images of each other: the former occur at market tops and have bearish implications, while the latter occur at market bottoms and have bullish implications. Moreover, observe that the first in the sequence of the defining five extrema is a maximum for bearish formations and a minimum for bullish formations.

**Pattern completion and the breaking of a neckline** In a simpler version of pattern definitions, patterns are considered complete as soon as the final extremum has been detected. While Lo, Mamaysky, and Wang consider only this simpler version, we examine both this simpler version and a more complicated one, in which the breaking of the neckline condition is included in the definition of the first eight patterns under consideration (HS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT).[8] For the bearish formations, the neckline is defined by a straight line drawn through the minima $E_2$ and $E_4$, while for the bullish formations it is defined by a straight line drawn through the maxima $E_2$ and $E_4$. If the breaking of the neckline condition is included in the definition of a bearish formation, then the formation is considered complete only when the price, moving downwards from the maximum $E_5$, closes under the neckline. Analogously, if the breaking of the neckline condition is included in the definition of a bullish formation, then the formation is considered complete only when the

[8]Including the breaking of the neckline condition in the definitions of DTOP and DBOT formations does not appear sensible given the fact that we will be focusing of short-horizon patterns (see, e.g., [42]).

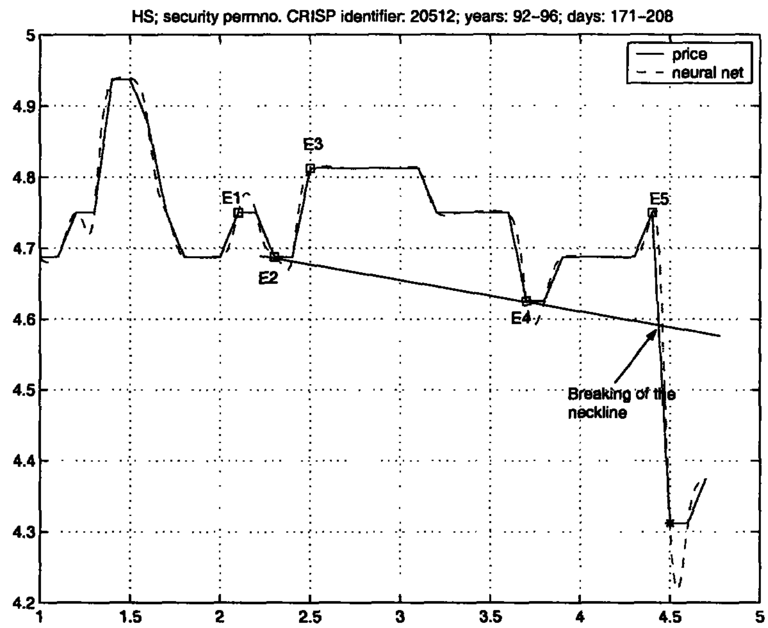


Figure 2-21: Breaking of the Neckline Case: Head-and-Shoulders Example

price, moving upwards from the minimum $E_5$, closes above the neckline. However, the exact amount of the closing violation of the neckline needed for a pattern to qualify as complete is widely disputed in the technical analysis literature. In our implementation, we classify a pattern as complete the instance the neckline is broken by any, however small, amount. Please see Figures 21-28 for illustration.

### 2.2.3 Scanning the neural network models for the presence of technical patterns

This final portion of our identification algorithm closely mimics that proposed by Lo, Mamaysky, and Wang.[9] In particular, given a sample of prices, $\{P_1, ..., P_T\}$, we construct rolling

[9]Please see [37, pp. 1718-1720].

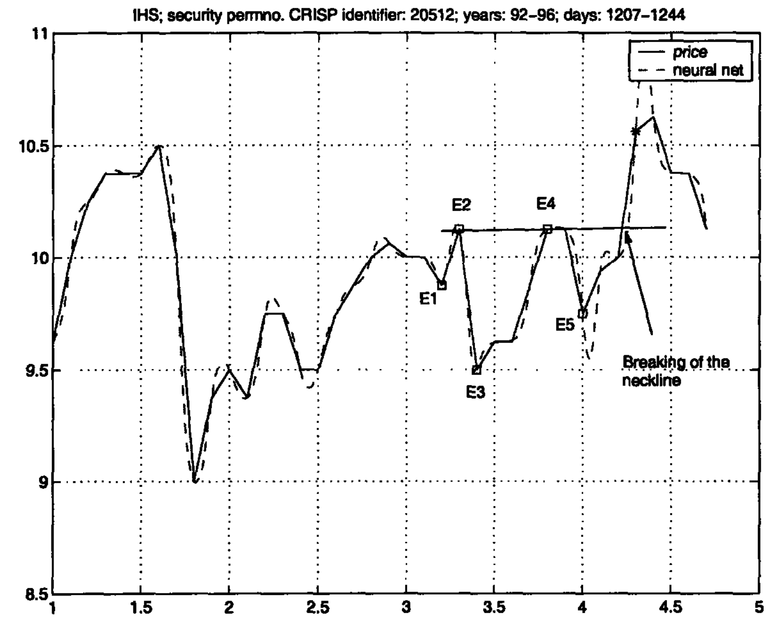


Figure 2-22: Breaking of the Neckline Case: Inverse Head-and-Shoulders Example

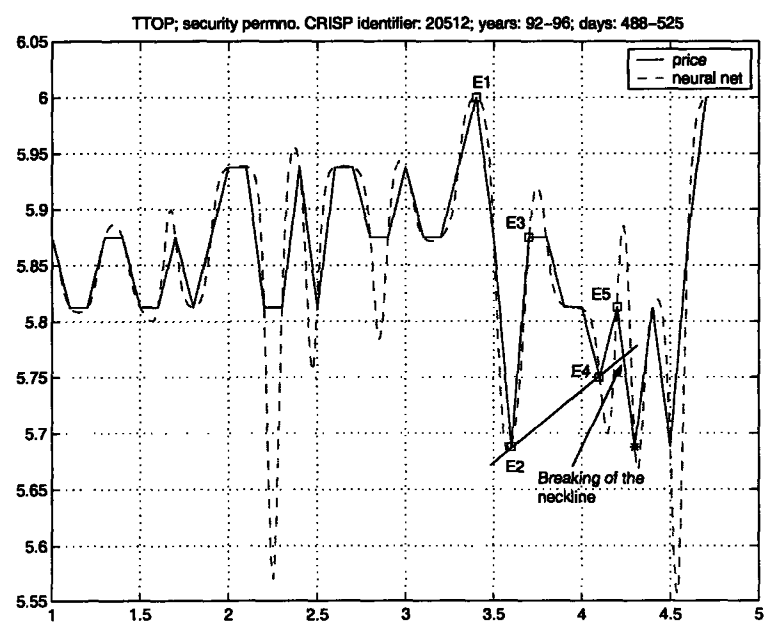


Figure 2-23: Breaking of the Neckline Case: Triangle Top Example

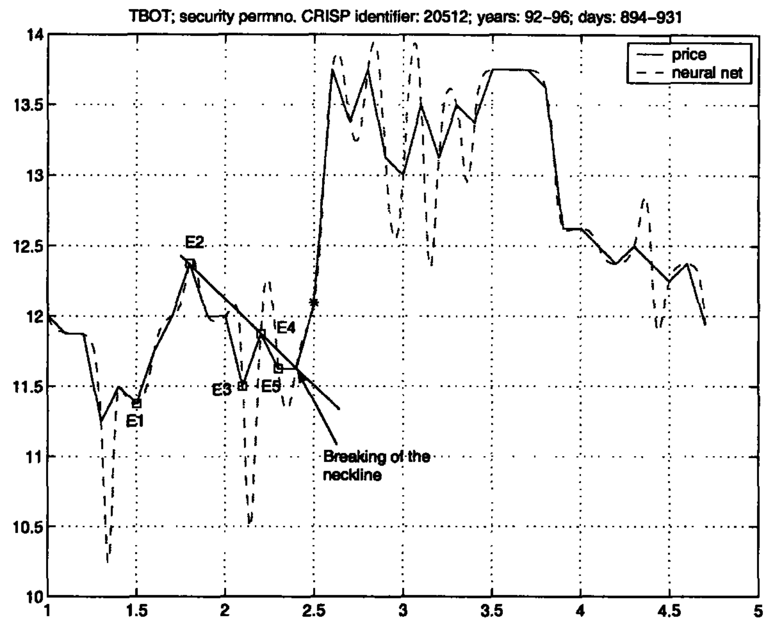


Figure 2-24: Breaking of the Neckline Case: Triangle Bottom Example

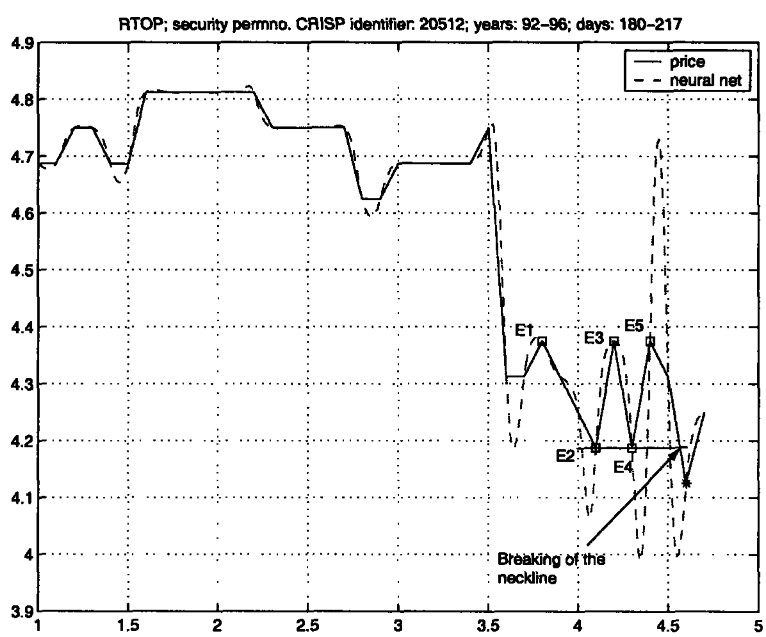


Figure 2-25: Breaking of the Neckline Case: Rectangle Top Example

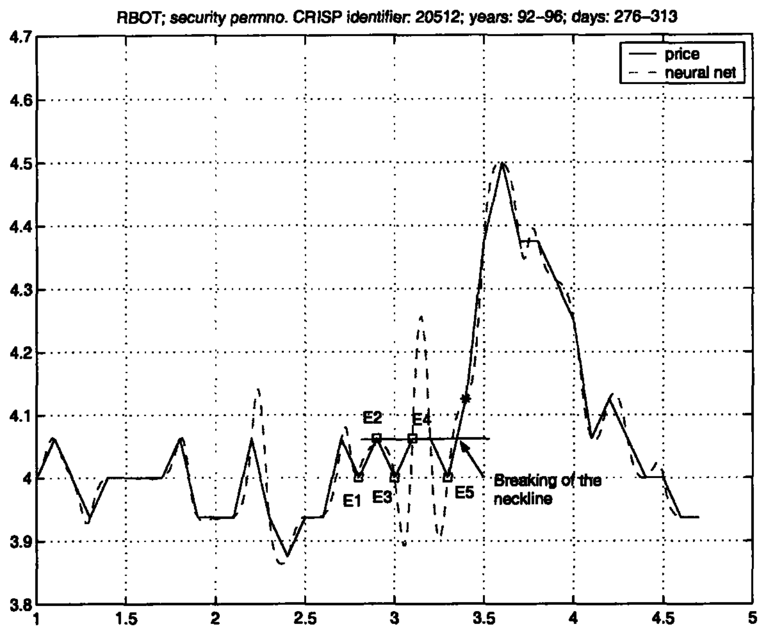


Figure 2-26: Breaking of the Neckline Case: Rectangle Bottom Example

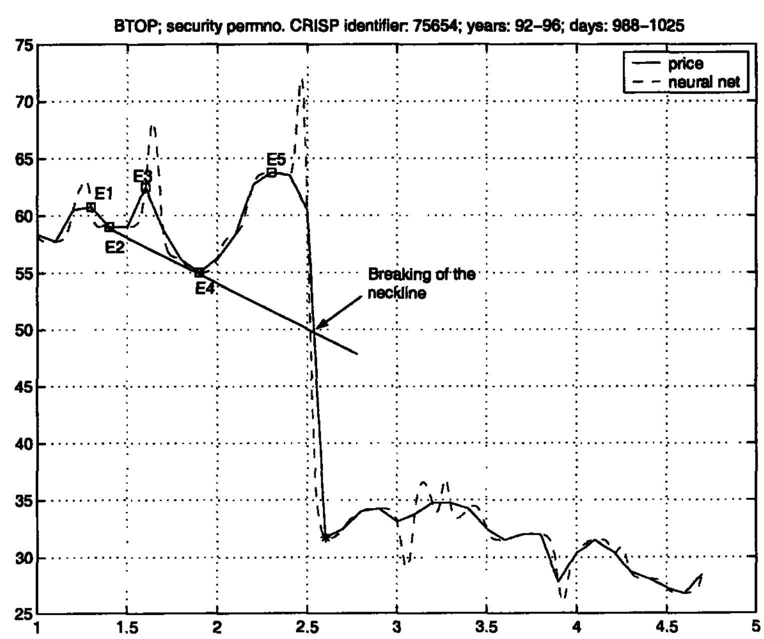


Figure 2-27: Breaking of the Neckline Case: Broadening Top Example

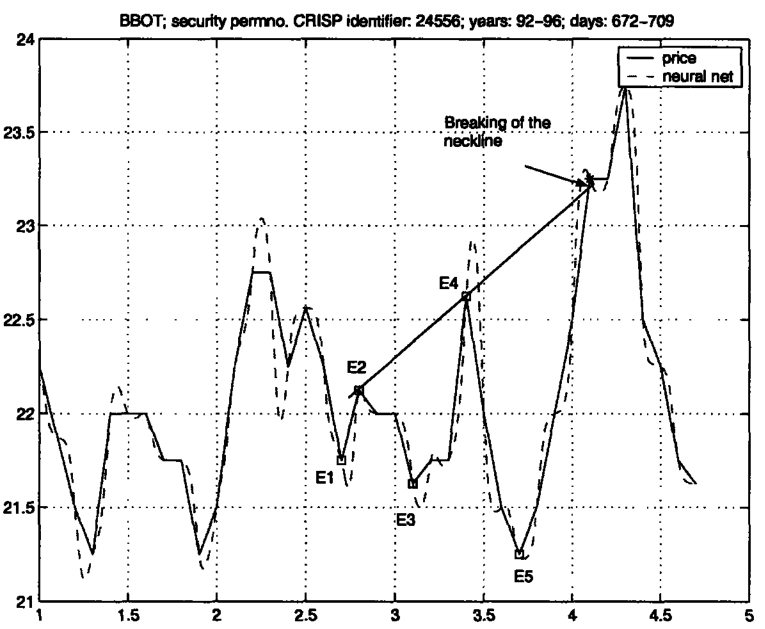


Figure 2-28: Breaking of the Neckline Case: Broadening Bottom Example

windows of data of length $l+d$, from $t$ to $t+l+d-1$, where $t$ varies from 1 to $T-l-d+1$, and where $l$ and $d$ are fixed parameters. As Lo, Mamaysky, and Wang explain, parameters $l$ and $d$ account for the fact that in practice a pattern is not detected as soon as it is completed, but that $d$ days must pass between the completion and the detection of a pattern. Following Lo, Mamaysky, and Wang, we focus on short-horizon patterns, and, just like they do, we set $l = 35$ and $d = 3$, so that each window spans $l + d = 38$ trading days. As the said authors point out, splitting the data into rolling subsamples rather than fitting a single smoothing estimator to the entire dataset is sensible, since in the latter case it would not be possible to distinguish signal from the noise.

Armed with a neural network model, $\hat{m}$, we then proceed to compute its local extrema by finding times $\tau$ such that $\text{Sgn}(\hat{m}'(\tau)) = -\text{Sgn}(\hat{m}'(\tau+1))$, where $\hat{m}'$ denotes the derivative of $\hat{m}$ with respect to $\tau$, and $\text{Sgn}(\cdot)$ stands for the signum function. If $\text{Sgn}(\hat{m}'(\tau)) = +1$ and $\text{Sgn}(\hat{m}'(\tau+1)) = -1$, we have a local maximum, while if $\text{Sgn}(\hat{m}'(\tau)) = -1$ and $\text{Sgn}(\hat{m}'(\tau+1)) = +1$, we have a local minimum. If prices stay the same for several consecutive days so that $\hat{m}'(\tau) = 0$ for a particular $\tau$, we look for an extremum by comparing $\text{Sgn}(\hat{m}'(\tau-1))$ and $Sgn(\hat{m}'(s))$, where $s = \inf\{s > \tau : \hat{m}'(s) \neq 0\}$. After we have identified all of the local extrema of a neural network in a given window, we proceed to identify the corresponding extrema in the original price series $\{P_t\}$, then scan the latter for the presence of one of the technical patterns previously defined.[10] For the first eight patterns under consideration, we also compute and store the date of the breaking of the neckline, the definition of which has been specified earlier. Finally, we repeat this procedure for each of the rolling subsample

[10]The neural network extrema that are not matched by the extrema in $\{P_t\}$ are discarded.

windows, until the end of the dataset is reached.

## 2.3 Evaluating the Significance of the Information Content of Technical Patterns

### 2.3.1 Comparing conditional and unconditional empirical distributions

To evaluate the informativeness of technical patterns, we again use the approach proposed by Lo, Mamaysky, and Wang in [37]. Namely, we compare the unconditional empirical distribution of returns with the corresponding conditional, or post-pattern, empirical distribution – if technical patterns are informative, then conditional and unconditional distributions should not be close. The distance between the distributions is measured in two ways, one, by the $\chi^2$ test of goodness-of-fit, and two, by the Kolmogorov-Smirnov test.

**The $\chi^2$ test of goodness-of-fit** Here we consider the null hypothesis that the returns are independently and identically distributed, and that the conditional and unconditional distributions are identical. For each pattern we compute the proportion of conditional returns falling into the decile $j$ of unconditional returns:

$$\hat{\delta}_j \equiv \frac{\text{number of conditional returns in decile j}}{\text{total number of conditional returns}}, \; j = 1, ..., 10. \tag{2.5}$$

Under the null hypothesis of equality, the expected proportion is 0.1. Moreover, the asymptotic distribution of $\hat{\delta}_j$ is given by

$$\sqrt{n}(\hat{\delta}_j - 0.10) \sim^a \mathcal{N}(0, 0.10(1-0.10)). \tag{2.6}$$

The asymptotic distribution of the corresponding goodness-of-fit statistic Q, as derived by Karl Pearson in 1900, is given by

$$Q \equiv \sum_{j=1}^{10} \frac{(n_j - 0.10n)^2}{0.10n} \sim^a \chi^2_9, \tag{2.7}$$

where $n_j$ is the number of observations in decile $j$, and $n$ is the total number of observations.[11]

**The Kolmogorov-Smirnov test for two samples** Consider two random samples, $X_1, ..., X_m$ and $Y_1, ..., Y_n$, each of which is *i.i.d.*, with cumulative distribution functions $F(x)$ and $G(x)$. We wish to test the null hypothesis that $F(x) = G(x)$, for $-\infty < x < \infty$, against the alternative that the null hypothesis is not true. Letting $F_m(x)$ and $G_n(x)$ denote the sample distribution functions calculated from the observed samples $X_1, ..., X_m$ and $Y_1, ..., Y_n$, we can construct statistics

$$D_{m,n} = sup_{-\infty<x<\infty}|F_m(x) - G_n(x)|, \text{ and} \tag{2.8}$$

[11]See, e.g., [20] or [37].

$$\gamma_{m,n} = \sqrt{\frac{mn}{m+n}})D_{m,n}. \tag{2.9}$$

Now, recall the result established by N.V. Smirnov (1939):

$$\lim_{n\to\infty,\ n\to\infty} \text{Prob}(\gamma_{m,n} \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k e^{-2k^2x^2},\ x > 0. \tag{2.10}$$

Kolmogorov-Smirnov test rejects the null hypothesis if the value statistic $\gamma_{m,n}$ is greater than the upper $100\alpha th$ percentile for the null distribution given by the above equation.

### 2.3.2 The data and the computation of the returns

**The data** The data comes from the Center for Research in Securities Prices (CRISP). It consists of daily price observations of a random sample of 25 Nasdaq stocks, from 1992 to 1996, with five stocks coming from each of the five market capitalization quintiles.

**Computing the returns** We start by subjecting each stock to our pattern recognition algorithm. For each pattern detected, we compute the one-day continuously compounded post-pattern returns $d$ days after the pattern has been completed, where we recall that the parameter $d$ is used to ensure that the post-pattern returns are computed entirely out-of-sample, that is, that no forward information is used in their computation.

Then, for each stock we also consider nonoverlapping intervals of length one, and compute the unconditional one-day continuously compounded returns. Finally, we compare the empirical distribution functions of conditional and unconditional returns using the previously described goodness-of-fit measures. Here it is important to note that by using the $\chi^2$ goodness-of-fit and Kolmogorov-Smirnov tests on the returns data, we are implicitly assuming that the returns are *i.i.d.*, which is not plausible, as Lo, Mamaysky, and Wang point out. However, as the said authors continue, the situation can be partially remedied by normalizing both conditional and unconditional returns of each security [37, p. 1719]. Following this suggestion, we standardize both conditional and unconditional returns of each individual stock, by subtracting its mean and dividing by its standard deviation.

### 2.3.3 Conditioning on volume

Technical analysts consider volume to be an important confirming indicator.[12] In general, volume is said to measure "the intensity or urgency behind the price move" [42, p. 162]. There are also many specific rules as to how the volume should behave as a pattern evolves, if it is to constitute a confirmation of that pattern. For example, in a downtrend, the volume should be heavier on the down moves and lighter on the bounces of a pattern, while the opposite should be true in an uptrend. Another example relates to the breaking of a neckline, which, as Murphy puts it, "should be accompanied by heavier trading activity if the signal given by that breakout is real" [42, p. 164]. Given the fact that volume plays such an important role in technical studies, we incorporate it into our investigation. However, following Lo, Mamaysky, and Wang, rather than considering all the nuances in the pattern-

[12]See, e.g., [42].

volume interaction, we simplify matters greatly in our analysis. Namely, for each stock, we compute its average share turnover during the first and second halves of each window, denoting the former by $\tau_1$, and the latter by $\tau_2$. An event such that $\tau_1 > 1.2\tau_2$ is labeled as "decreasing volume," while an even such that $\tau_2 > 1.2\tau_1$ is labeled as "increasing volume." We then construct conditional returns that are conditioned both on the occurrence of a pattern and the occurrence of a decreasing or increasing volume event.

## 2.4 Empirical Results and their Interpretation

### 2.4.1 Summary of cases to be investigated empirically

To sum up, we have three main cases to consider: (1) the case where the pattern recognition algorithm employs a lower degree of smoothing, (2) the case where it employs a higher degree of smoothing, and (3) the case where the low degree of smoothing is coupled with the breaking of the neckline requirement. For each of these three cases, the tests of the equality of the conditional and unconditional one-day normalized return distributions are performed with three different definitions of the conditional returns: (1) a distribution that is conditioned on the occurrence of one of the ten technical patterns under consideration, (2) a distribution that is conditioned on the occurrence of both one of the ten technical patterns and an increasing volume trend event, and (3) a distribution that is conditioned on the occurrence of both one of the ten technical patterns and a decreasing volume trend event.

### 2.4.2 Summary statistics

Tables 1 to 3 report frequency counts of the patterns detected for all the stocks together and in separate market capitalization quintiles, from 1992 to 1996. Table 1 refers to the case where the pattern recognition algorithm employs a lower degree of smoothing, Table 2 refers to the case where the pattern recognition algorithm employs a higher degree of smoothing, while Table 3 concerns the case where the lower degree of smoothing is coupled with the breaking of the neckline condition for the first eight patterns under consideration. We start by observing that the most frequent are RBOT patterns in all three cases. In the subsequent discussion, we will use these three tables to examine the effects that the change in the degree of smoothing, as well as the inclusion of the breaking of the neckline condition in the pattern definions, have on the frequency counts of these patterns, where the former effect is analyzed on comparison of Tables 1 and 2, and the latter on comparison of Tables 1 and 3.

Table 2.1: Frequency counts for 10 technical indicators detected among the Nasdaq stocks for 1992 to 1996, in market capitalization quintiles, where neural networks with a **lower degree of smoothing** were employed in the pattern recognition algorithm. As the "Sample" column indicates, the frequency counts are reported in three ways: (1) unconditional of volume, (2) conditioned on decreasing volume trend ('$\tau(\searrow)$'), and (3) conditioned on increasing volume trend ('$\tau(\nearrow)$').

| Sample | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Entire | 23944 | 5680 | 3492 | 3067 | 2898 | 7213 | 9217 | 1560 | 1962 | 939 | 959 |
| $\tau(\searrow)$ | – | 2390 | 1232 | 1350 | 1170 | 3028 | 3921 | 621 | 778 | 331 | 477 |
| $\tau(\nearrow)$ | – | 2050 | 1322 | 958 | 940 | 2737 | 3445 | 567 | 727 | 307 | 175 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4291 | 1008 | 464 | 175 | 120 | 2700 | 3016 | 97 | 230 | 125 | 89 |
| $\tau(\searrow)$ | – | 456 | 177 | 81 | 53 | 1132 | 1233 | 15 | 94 | 35 | 48 |
| $\tau(\nearrow)$ | – | 359 | 174 | 77 | 55 | 1104 | 1245 | 70 | 85 | 48 | 30 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4600 | 918 | 452 | 420 | 410 | 1675 | 2357 | 257 | 422 | 159 | 166 |
| $\tau(\searrow)$ | – | 343 | 193 | 189 | 177 | 730 | 1022 | 99 | 156 | 62 | 96 |
| $\tau(\nearrow)$ | – | 431 | 172 | 138 | 148 | 641 | 945 | 95 | 199 | 74 | 35 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4816 | 944 | 411 | 605 | 475 | 835 | 1494 | 298 | 399 | 227 | 126 |
| $\tau(\searrow)$ | – | 378 | 147 | 270 | 213 | 324 | 636 | 119 | 162 | 69 | 82 |
| $\tau(\nearrow)$ | – | 335 | 157 | 163 | 179 | 330 | 539 | 134 | 152 | 62 | 23 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4819 | 1443 | 958 | 578 | 759 | 1441 | 1749 | 472 | 364 | 203 | 246 |
| $\tau(\searrow)$ | – | 653 | 356 | 229 | 336 | 647 | 836 | 222 | 168 | 98 | 106 |
| $\tau(\nearrow)$ | – | 526 | 371 | 185 | 203 | 484 | 605 | 141 | 124 | 70 | 49 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 5418 | 1367 | 1207 | 1289 | 1134 | 562 | 601 | 436 | 547 | 225 | 332 |
| $\tau(\searrow)$ | – | 560 | 359 | 581 | 391 | 195 | 194 | 166 | 198 | 67 | 145 |
| $\tau(\nearrow)$ | – | 399 | 448 | 395 | 355 | 178 | 111 | 127 | 167 | 53 | 38 |

Table 2.2: Frequency counts for 10 technical indicators detected among the Nasdaq stocks for 1992 to 1996, in market capitalization quintiles, where neural networks with a **higher degree of smoothing** were employed in the pattern recognition algorithm. As the "Sample" column indicates, the frequency counts are reported in three ways: (1) unconditional of volume, (2) conditioned on decreasing volume trend ('$\tau(\searrow)$'), and (3) conditioned on increasing volume trend ('$\tau(\nearrow)$').

| Sample | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Entire | 23944 | 752 | 508 | 920 | 847 | 872 | 1314 | 517 | 567 | 590 | 531 |
| $\tau(\searrow)$ | – | 321 | 205 | 426 | 357 | 409 | 526 | 180 | 258 | 236 | 257 |
| $\tau(\nearrow)$ | – | 302 | 164 | 243 | 251 | 311 | 558 | 212 | 191 | 191 | 138 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4291 | 75 | 51 | 68 | 64 | 296 | 383 | 11 | 41 | 88 | 53 |
| $\tau(\searrow)$ | – | 26 | 18 | 29 | 38 | 127 | 149 | 3 | 18 | 41 | 23 |
| $\tau(\nearrow)$ | – | 33 | 24 | 25 | 12 | 125 | 173 | 6 | 20 | 26 | 21 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4600 | 216 | 114 | 142 | 133 | 238 | 442 | 136 | 112 | 108 | 122 |
| $\tau(\searrow)$ | – | 77 | 53 | 87 | 70 | 102 | 157 | 47 | 71 | 44 | 62 |
| $\tau(\nearrow)$ | – | 114 | 28 | 28 | 44 | 81 | 202 | 62 | 25 | 48 | 30 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4816 | 196 | 128 | 255 | 182 | 174 | 286 | 128 | 155 | 132 | 84 |
| $\tau(\searrow)$ | – | 90 | 51 | 125 | 75 | 79 | 117 | 38 | 61 | 56 | 47 |
| $\tau(\nearrow)$ | – | 56 | 46 | 62 | 70 | 59 | 113 | 59 | 57 | 37 | 23 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4819 | 189 | 163 | 245 | 308 | 145 | 187 | 146 | 159 | 148 | 161 |
| $\tau(\searrow)$ | – | 89 | 65 | 94 | 108 | 91 | 97 | 62 | 71 | 62 | 69 |
| $\tau(\nearrow)$ | – | 79 | 51 | 74 | 92 | 40 | 66 | 49 | 59 | 45 | 42 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 5418 | 76 | 52 | 210 | 160 | 19 | 16 | 96 | 100 | 114 | 111 |
| $\tau(\searrow)$ | – | 39 | 18 | 91 | 66 | 10 | 6 | 30 | 37 | 33 | 56 |
| $\tau(\nearrow)$ | – | 20 | 15 | 54 | 33 | 6 | 4 | 36 | 30 | 35 | 22 |

Table 2.3: Frequency counts for 10 technical indicators detected among the Nasdaq stocks for 1992 to 1996, in market capitalization quintiles, where the definitions of HS, IHS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT patterns include the **breaking of the neckline** condition, and where a lower degree of smoothing is used. As the "Sample" column indicates, the frequency counts are reported in three ways: (1) unconditional of volume, (2) conditioned on decreasing volume trend ('$\tau(\searrow)$'), and (3) conditioned on increasing volume trend ('$\tau(\nearrow)$').

| Sample | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Entire | 23944 | 2859 | 1973 | 2614 | 2514 | 3142 | 4280 | 85 | 96 | 939 | 959 |
| $\tau(\searrow)$ | – | 1193 | 647 | 1172 | 1028 | 1247 | 1690 | 47 | 23 | 331 | 477 |
| $\tau(\nearrow)$ | – | 1026 | 783 | 794 | 824 | 1226 | 1644 | 9 | 41 | 307 | 175 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4291 | 437 | 207 | 145 | 111 | 1167 | 1332 | 0 | 0 | 125 | 89 |
| $\tau(\searrow)$ | – | 225 | 101 | 72 | 52 | 481 | 504 | 0 | 0 | 35 | 48 |
| $\tau(\nearrow)$ | – | 137 | 56 | 60 | 47 | 459 | 576 | 0 | 0 | 48 | 30 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4600 | 450 | 255 | 389 | 346 | 641 | 1011 | 1 | 26 | 159 | 166 |
| $\tau(\searrow)$ | – | 156 | 120 | 183 | 147 | 261 | 415 | 0 | 6 | 62 | 96 |
| $\tau(\nearrow)$ | – | 214 | 97 | 123 | 131 | 283 | 424 | 1 | 13 | 74 | 35 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4816 | 486 | 292 | 526 | 397 | 470 | 715 | 0 | 47 | 227 | 126 |
| $\tau(\searrow)$ | – | 191 | 98 | 228 | 176 | 172 | 239 | 0 | 15 | 69 | 82 |
| $\tau(\nearrow)$ | – | 192 | 121 | 149 | 152 | 208 | 284 | 0 | 23 | 62 | 23 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 4819 | 714 | 480 | 502 | 663 | 521 | 871 | 25 | 4 | 203 | 246 |
| $\tau(\searrow)$ | – | 330 | 148 | 203 | 294 | 225 | 409 | 7 | 2 | 98 | 106 |
| $\tau(\nearrow)$ | – | 271 | 199 | 151 | 173 | 170 | 297 | 7 | 0 | 70 | 49 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Entire | 5418 | 772 | 739 | 1052 | 997 | 343 | 351 | 59 | 19 | 225 | 332 |
| $\tau(\searrow)$ | – | 291 | 180 | 486 | 359 | 108 | 123 | 40 | 0 | 67 | 145 |
| $\tau(\nearrow)$ | – | 212 | 310 | 311 | 321 | 106 | 63 | 1 | 5 | 53 | 38 |

Comparing Tables 1 and 3, we observe that the triangle formations are the least sensitive, while the broadening formations are the most sensitive to whether or not the breaking of the neckline condition is included in their definitions. Specifically, defining a pattern as complete only after a breaking of the neckline has occurred reduces the total frequency counts by about 15% for TTOP and TBOT patterns, by about 50% for HS and IHS patterns, by about 60% for RTOP and RBOT patterns, and by more than 95% for BTOP and BBOT patterns. Comparing Tables 1 and 2, we note that the pattern recognition based on more smoothing reduces total frequency counts by 85 – 90% for HS, IHS, RTOP, and RBOT patterns, by about 70% for TTOP, TBOT, BTOP, and BBOT patterns, and by about 40% for DTOP and DBOT patterns.

These results make a lot of sense. First of all, the triangle and the broadening formations are similar in that they both react in an extreme way to the inclusion of the breaking of the neckline condition in their definitions, with the triangle formations being the least sensitive, and the broadening formations being the most sensitive of all the patterns considered. Such behavior may be understood by examining the geometrical shapes of these patterns. A triangle consists of the upper descending trendline and the lower ascending trendline which meet at the apex on the right. Since these trendlines are converging, it is easy for the price to break outside the formation and thereby break the neckline. On the contrast, in the broadening formation the trendlines actually diverge, making it hard for the price to break outside the formation, that is, to break the neckline. Moreover, these two types of formations undergo the same amount of percent reduction in their frequency counts when they are switched from a lower to a higher degree of smoothing, further emphasizing the possibility of the existence of some inherent analogies between them, which should be examined more closely in future research.

The magnitude of the reduction in the number of broadening formations detected between Tables 1 and 3 (more than 95%) suggests that the breaking of the neckline condition may well be an important element of their definitions, since having few of them agrees with their characterization as "unusual" and "relatively rare" by technical analysts [42, p. 140]. It is also insightful to note that for the broadening top, the two smallest market capitalization quintiles contain most of the patterns. This is especially evident in Table 2, where the three largest quintiles together contain only two patterns. These results seem to support Murphy's statement that a broadening top "represents a market that is out of control and unusually emotional," as these are likely to be the characteristics of small cap firms [42, pp. 140-141].

Another interesting observation is that for most of the pattern types under consideration, frequency counts reduce as we move from Table 1 to Table 3, and further reduce as we move from Table 3 to Table 2. The only exceptions are broadening tops and bottoms, where the frequency counts reduce as we move from Table 1 to Table 2, and further reduce as we move from Table 2 to Table 3. This, coupled with the dramatic extent of their total reduction, suggests yet again that there may exist something unusual about the nature of these patterns and the kind of market conditions that they characterize, lending further support to the above-mentioned statement that a broadening top "represents a market that is out of control and unusually emotional" [42, pp. 140-141].

The fact that the inclusion of the breaking of the neckline condition in the definitions of HS and IHS patterns yields a 50% reduction in their frequency counts also makes sense in terms of their geometry, since for these patterns the neckline neither always eases nor always deters the breakout, but is equally likely to either descend, ascend, or stay flat. Moreover, the amount of change induced by the inclusion of the breaking of the neckline condition in pattern definitions is comparable for head-and-shoulders and rectangle formations, which also change by a similar amount when the pattern recognition algorithm switches from a lower to a higher degree of smoothing. Noting, in addition, that RBOT, RTOP, and HS are the three most frequent pattern types in Tables 1 and 3, we suspect that, while technical analysis literature mostly categorizes rectangles together with triangles rather than with head-and-shoulders in terms of their duration and forecasting value, there may exist some inherent similarities between the rectangle and the head-and-shoulders formations, which become apparent only with a certain degree of smoothing, and which should be investigated further.

Furthermore, the near equality of the reduction rates for the corresponding top and bottom pattern types, both from Table 1 to Table 2 and from Table 1 to Table 3, is what one would expect, since they are just the mirror images of each other. Finally, we note that these reduction rates remain mostly the same regardless of whether the counts are unconditional of volume, or conditioned on a decreasing or increasing volume trend.[13] Although no definitive conclusion can be drawn from this simple observation, it does make us question the extent of the incremental information that conditioning on increasing or decreasing volume trend

[13]The only exception is seen in the case of DBOT on increasing volume.

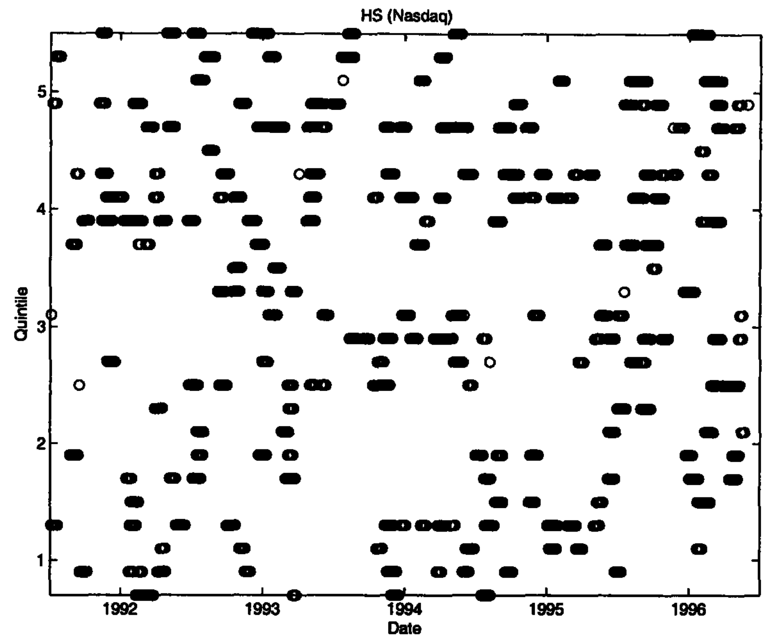


Figure 2-29: Lower Degree of Smoothing Case: Distribution of HS Patterns

provides, an issue which will be investigated later in this thesis.

We also examine the detected patterns for the evidence of clustering, both by date and by size quintiles. For this purpose, for each of the three cases under consideration, we plot the cross-sectional and time-series distributions of each pattern, so that, on a given graph, the vertical axis stands for the size quintile, the horizontal axis stands for the date, and each circle represents a detected pattern (please see Figures 29-56). Upon the examination of these displays, we conclude that patterns are neither clustered in time nor in cross-section.

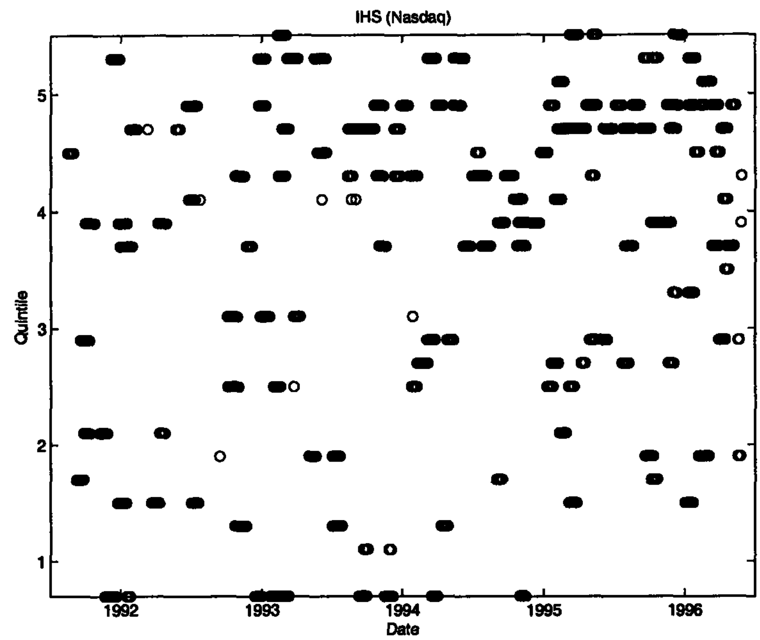


Figure 2-30: Lower Degree of Smoothing Case: Distribution of IHS Patterns

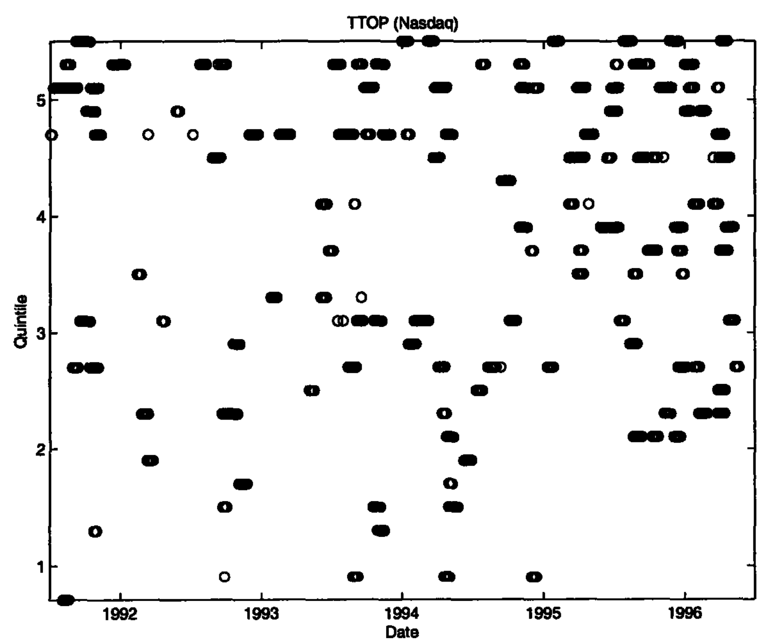


Figure 2-31: Lower Degree of Smoothing Case: Distribution of TTOP Patterns

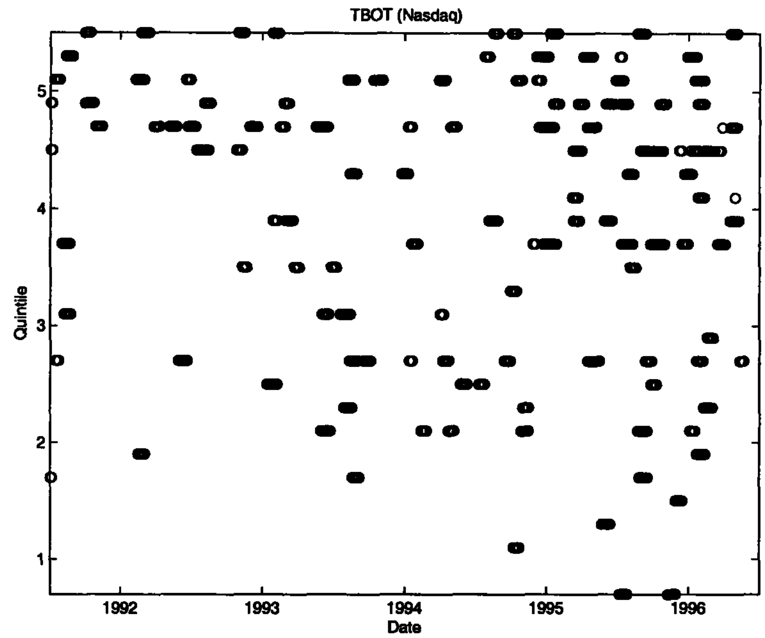


Figure 2-32: Lower Degree of Smoothing Case: Distribution of TBOT Patterns

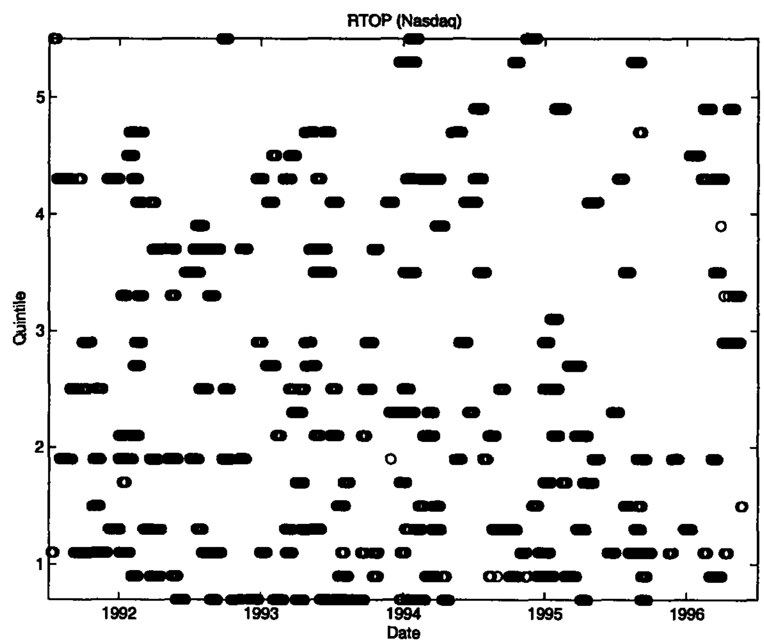


Figure 2-33: Lower Degree of Smoothing Case: Distribution of RTOP Patterns

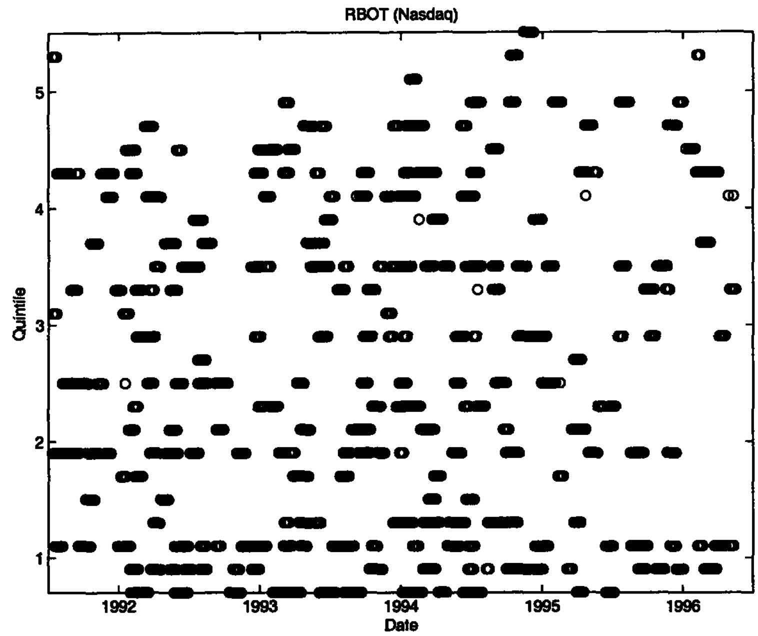


Figure 2-34: Lower Degree of Smoothing Case: Distribution of RBOT Patterns

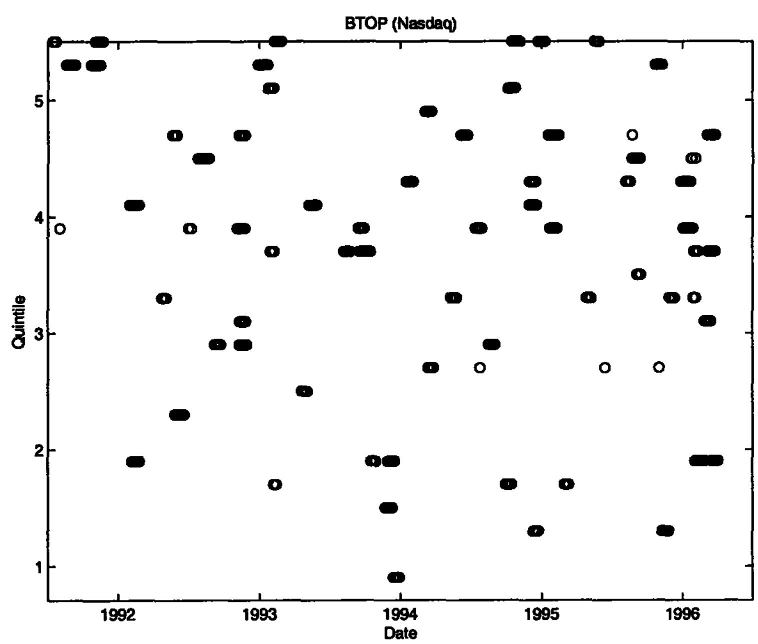


Figure 2-35: Lower Degree of Smoothing Case: Distribution of BTOP Patterns

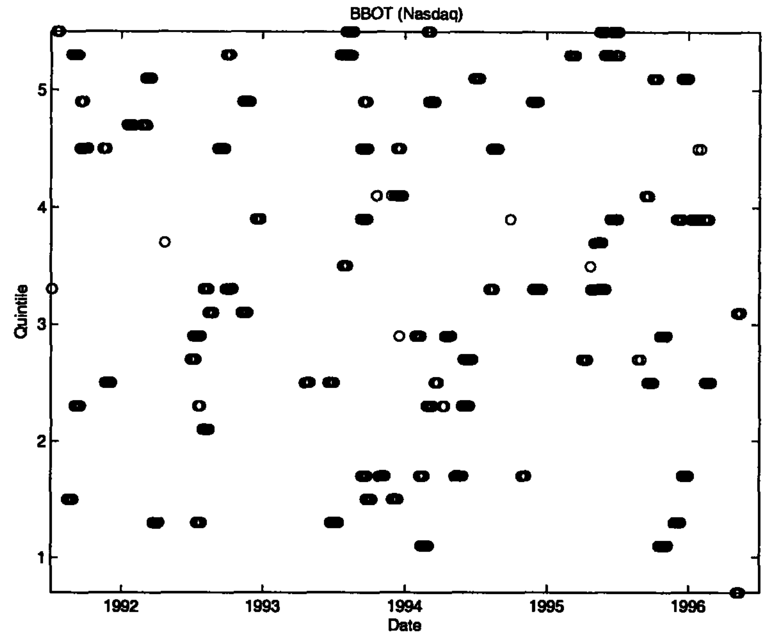


Figure 2-36: Lower Degree of Smoothing Case: Distribution of BBOT Patterns

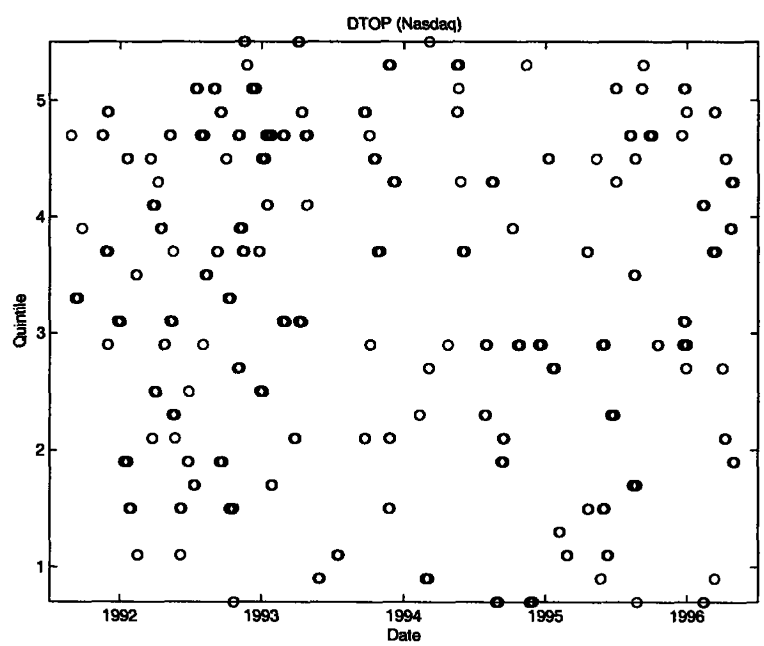


Figure 2-37: Lower Degree of Smoothing Case: Distribution of DTOP Patterns

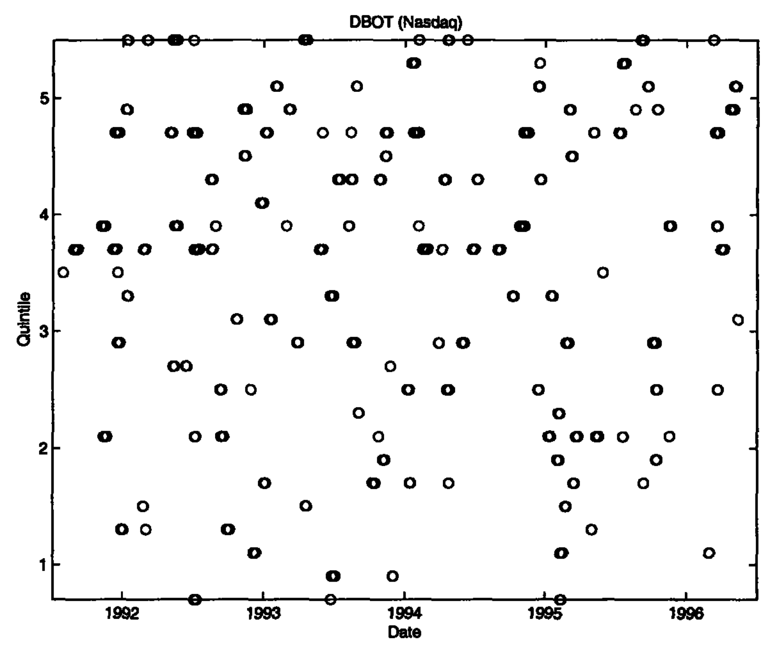


Figure 2-38: Lower Degree of Smoothing Case: Distribution of DBOT Patterns

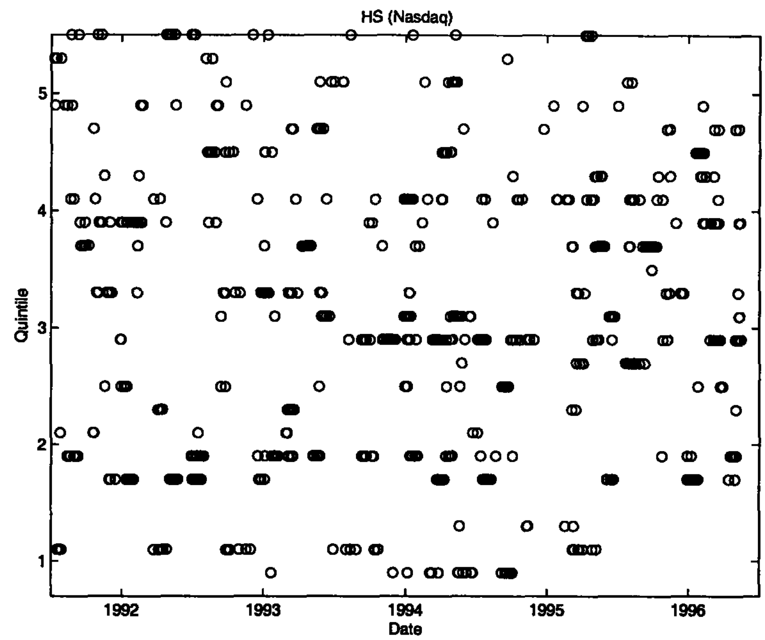


Figure 2-39: Higher Degree of Smoothing Case: Distribution of HS Patterns

We next report the summary statistics (means, standard deviations, skewness, and sample kurtosis) of the unconditional (raw) returns, and the returns conditional on the occurrence of one of the technical patterns under consideration for all the Nasdaq stocks form our sample and in size quintiles. These statistics are presented for each of the three cases under consideration: Tables 4 to 6 refer to the case where the pattern recognition algorithm employs a lower degree of smoothing, the case where it is based on a higher degree of smoothing, and the case where a lower degree of smoothing is coupled with the breaking of the neckline requirement, respectively.

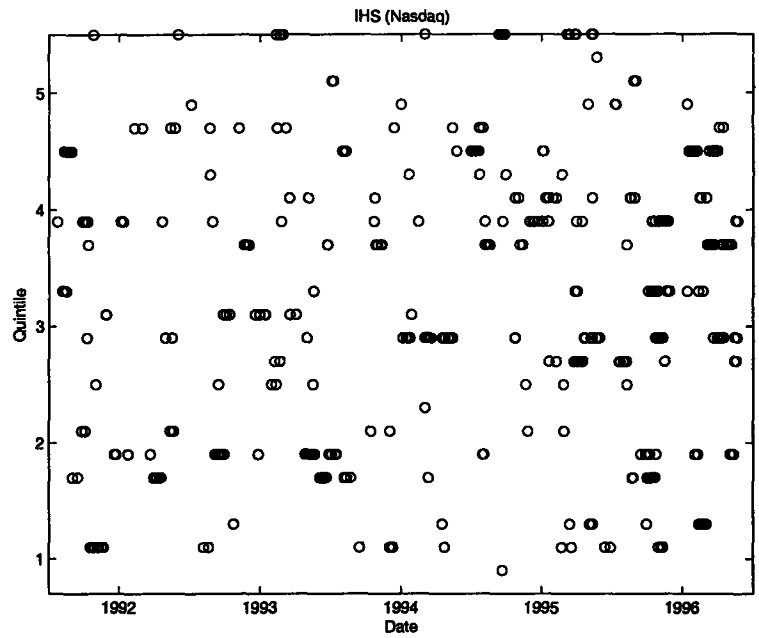


Figure 2-40: Higher Degree of Smoothing Case: Distribution of IHS Patterns

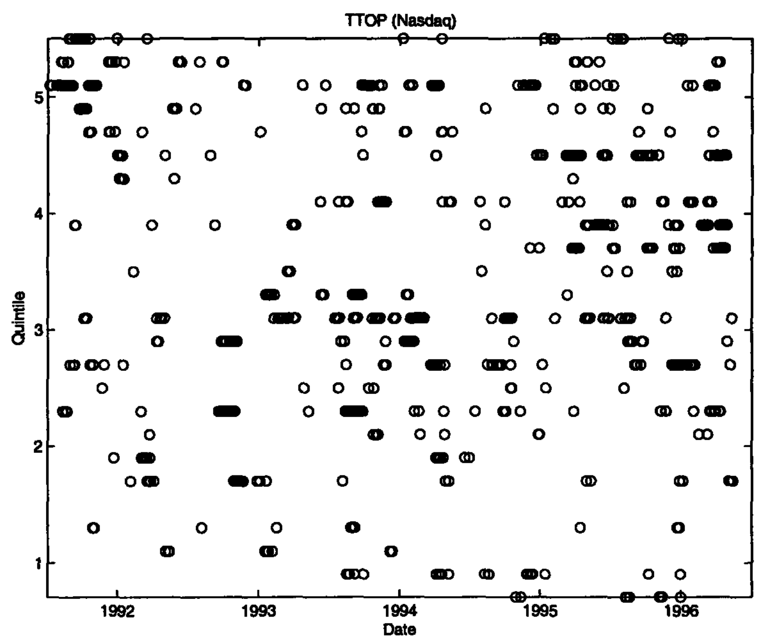


Figure 2-41: Higher Degree of Smoothing Case: Distribution of TTOP Patterns

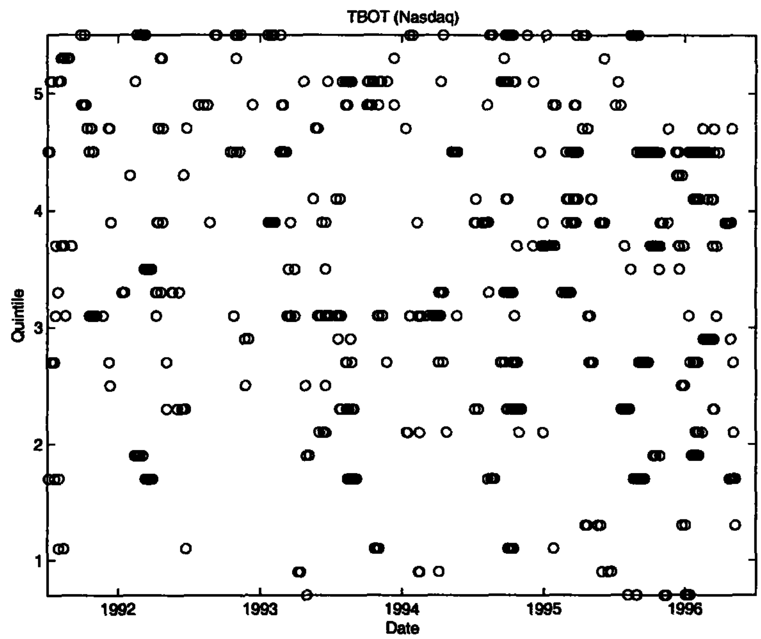


Figure 2-42: Higher Degree of Smoothing Case: Distribution of TBOT Patterns

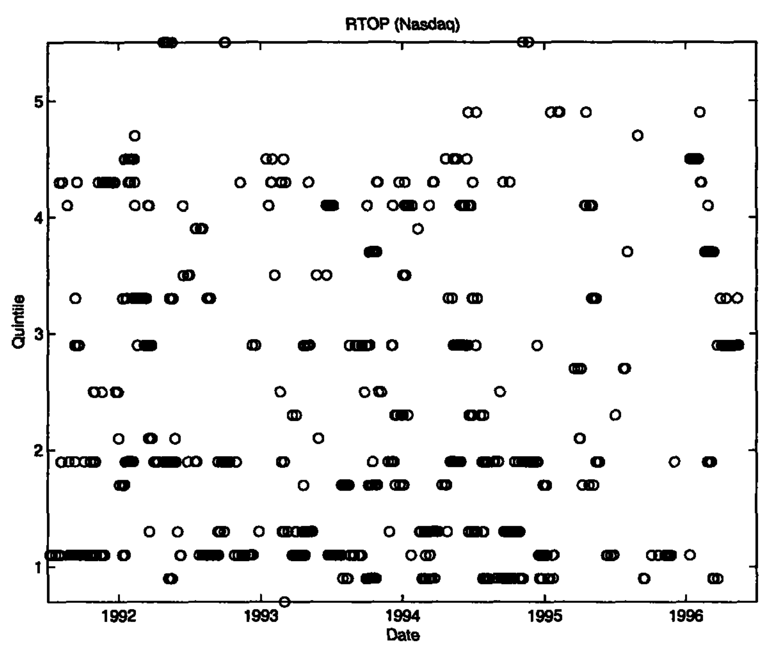


Figure 2-43: Higher Degree of Smoothing Case: Distribution of RTOP Patterns

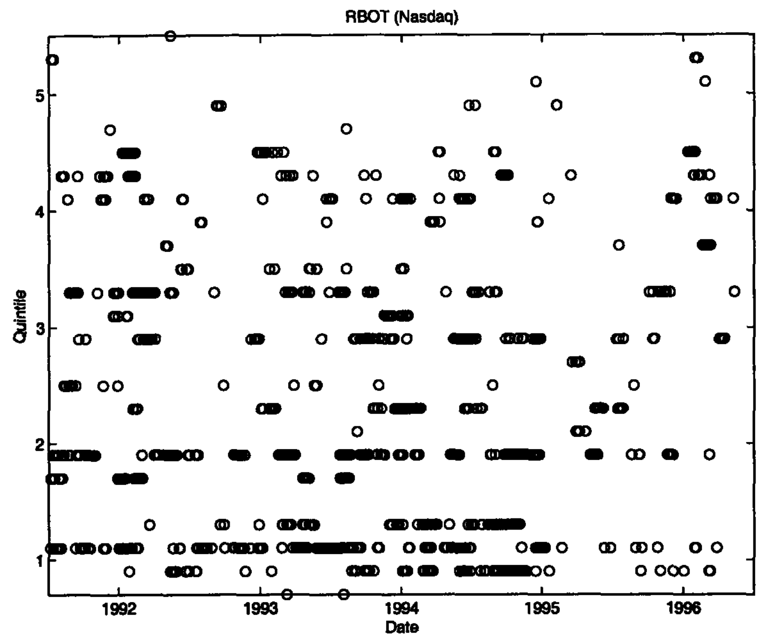


Figure 2-44: Higher Degree of Smoothing Case: Distribution of RBOT Patterns

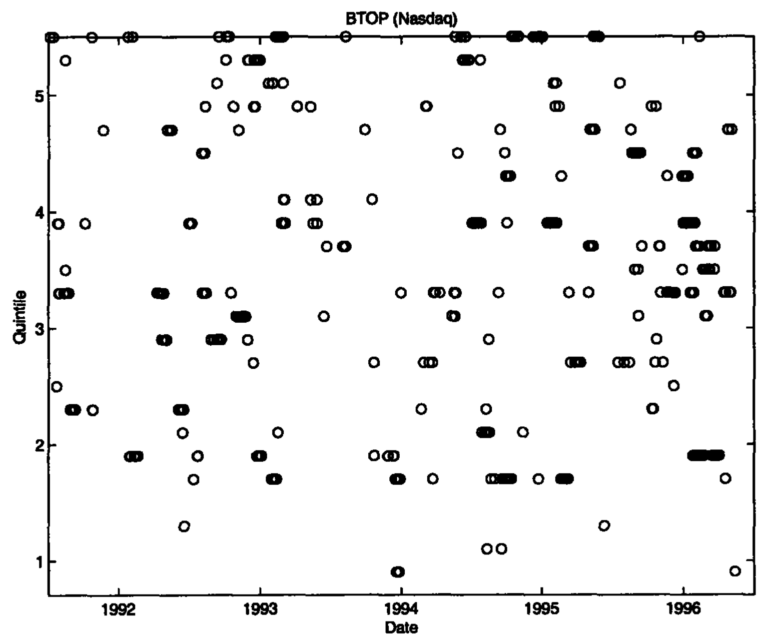


Figure 2-45: Higher Degree of Smoothing Case: Distribution of BTOP Patterns

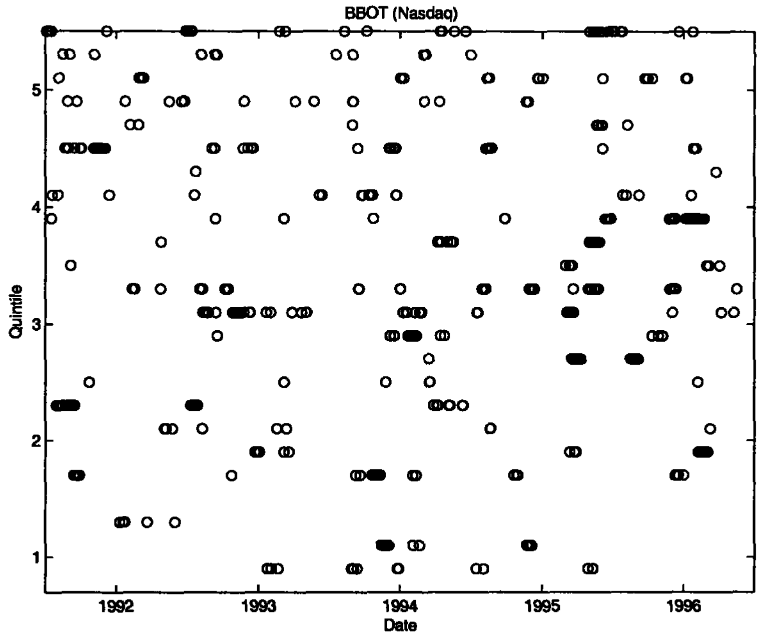


Figure 2-46: Higher Degree of Smoothing Case: Distribution of BBOT Patterns

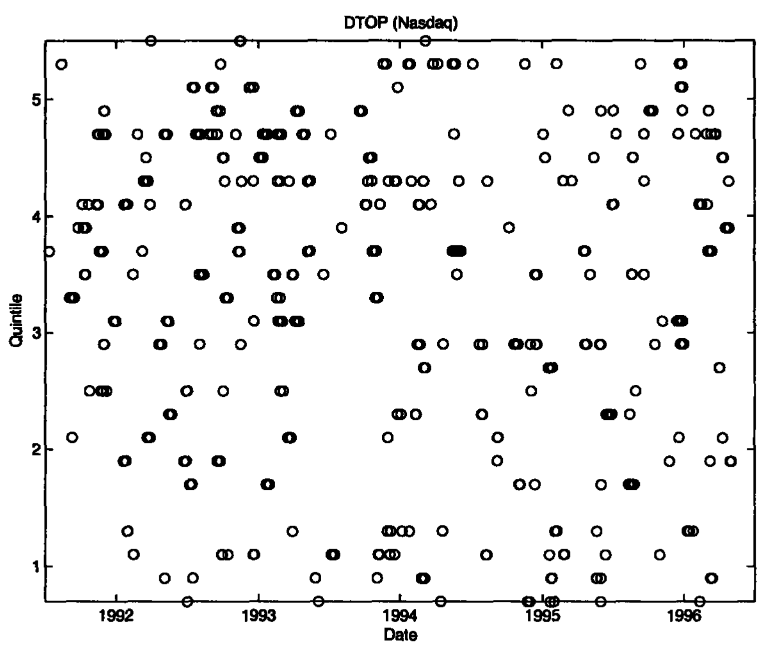


Figure 2-47: Higher Degree of Smoothing Case: Distribution of DTOP Patterns

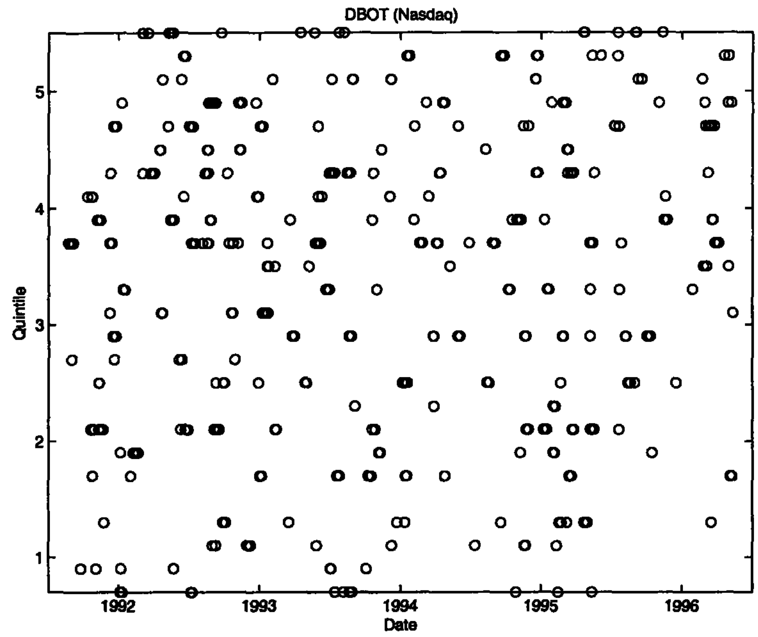


Figure 2-48: Higher Degree of Smoothing Case: Distribution of DBOT Patterns

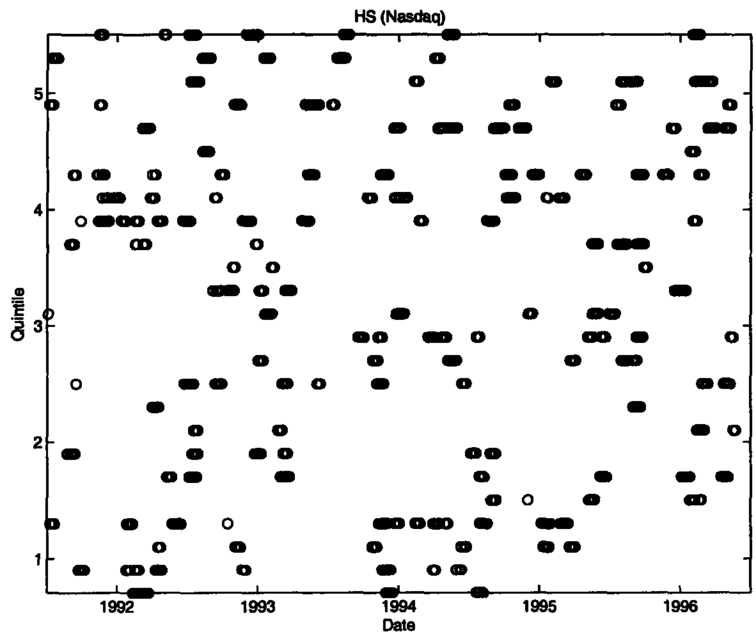


Figure 2-49: Breaking of the Neckline Case: Distribution of HS Patterns

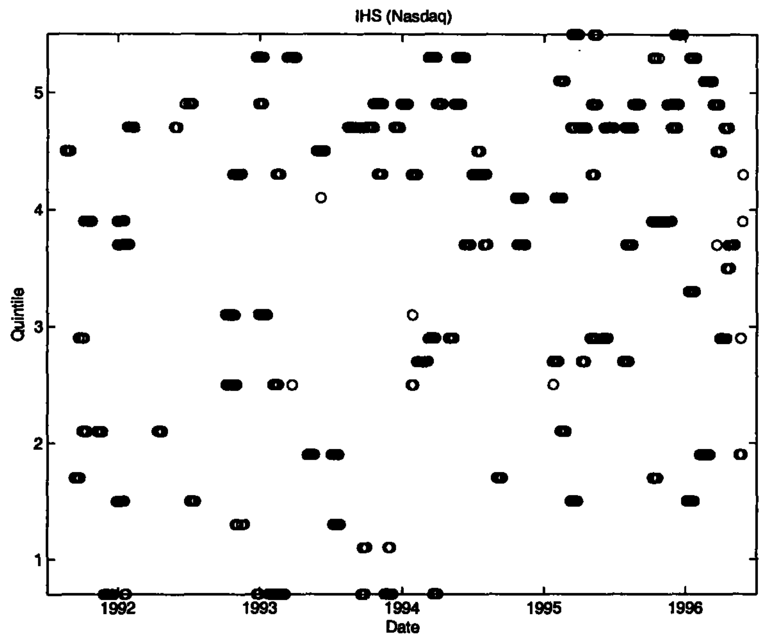


Figure 2-50: Breaking of the Neckline Case: Distribution of IHS Patterns

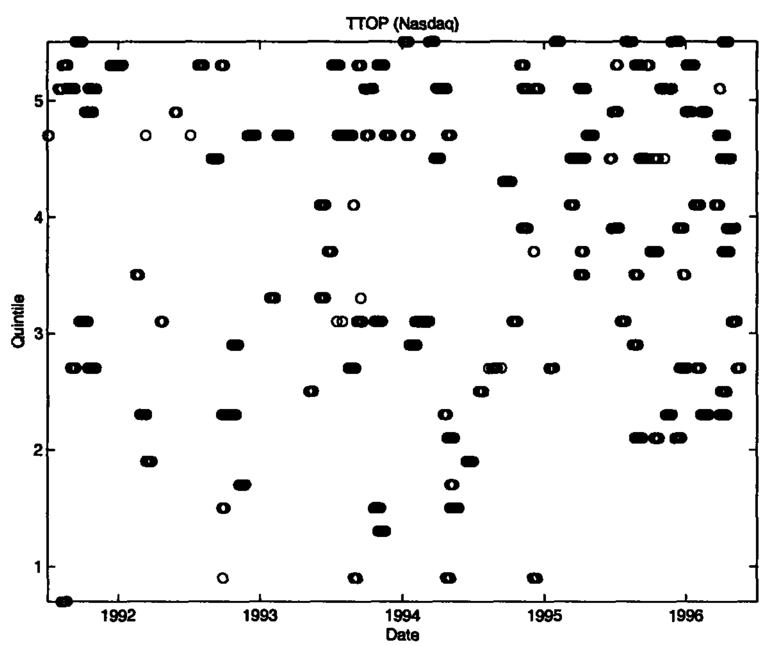


Figure 2-51: Breaking of the Neckline Case: Distribution of TTOP Patterns

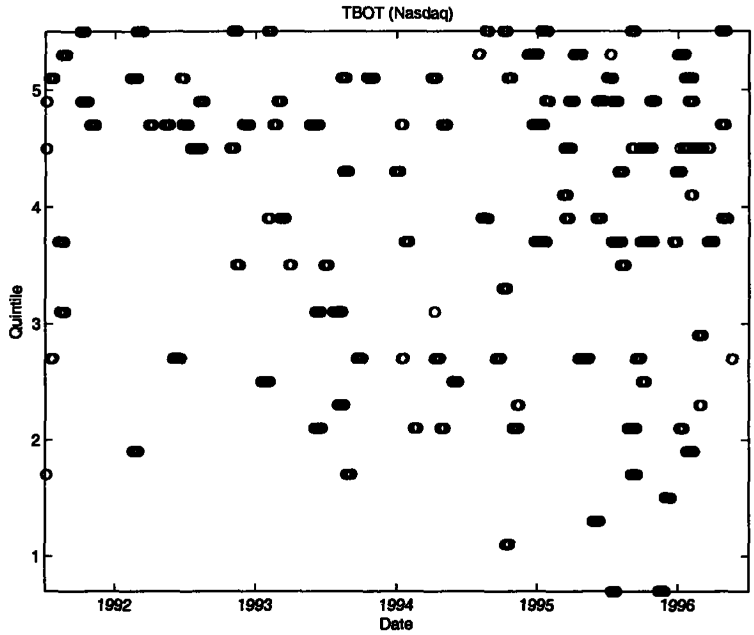


Figure 2-52: Breaking of the Neckline Case: Distribution of TBOT Patterns

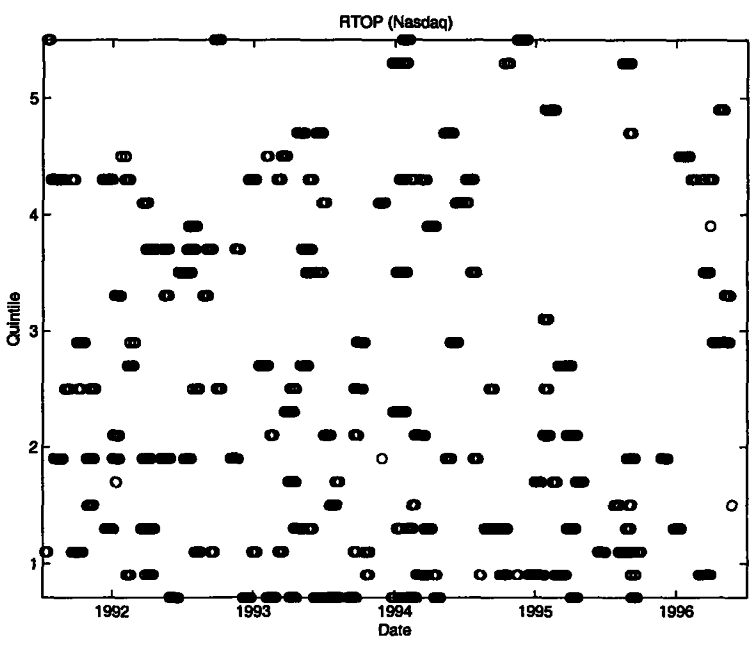


Figure 2-53: Breaking of the Neckline Case: Distribution of RTOP Patterns

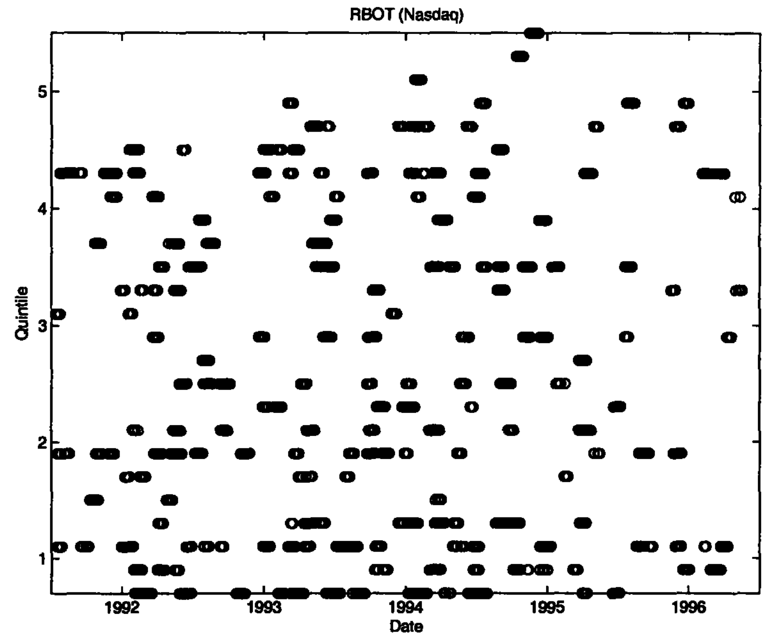


Figure 2-54: Breaking of the Neckline Case: Distribution of RBOT Patterns

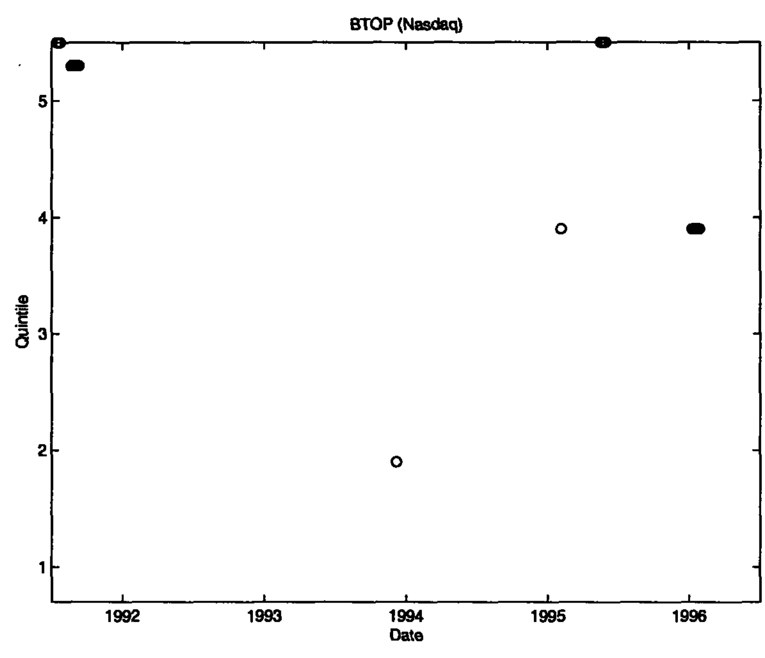


Figure 2-55: Breaking of the Neckline Case: Distribution of BTOP Patterns

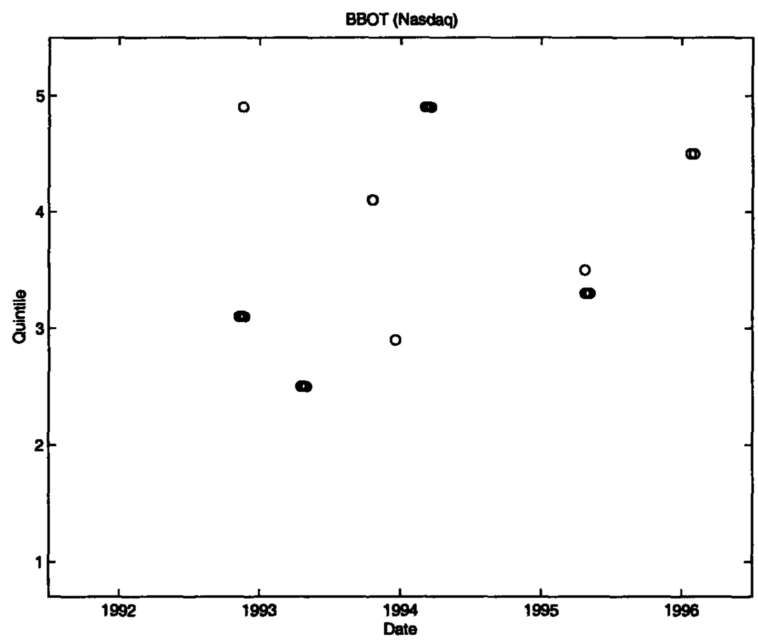


Figure 2-56: Breaking of the Neckline Case: Distribution of BBOT Patterns

Table 2.4: Summary statistics of raw and conditional one-day normalized returs for all of the 25 Nasdaq stocks from our sample and in size quintiles, from 1992 to 1996, where neural networks with a **lower degree of smoothing** were employed in the pattern recognition algorithm. The conditional returns are conditioned on the occurence of each of the technical patterns under consideration.

| Moment | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | −0.0000 | −0.0044 | −0.0049 | −0.0014 | −0.0035 | 0.0064 | 0.0269 | −0.0076 | 0.0002 | −0.0120 |
| S.D. | 0.9995 | 0.9979 | 0.9968 | 0.9916 | 0.9844 | 0.9984 | 0.9987 | 0.9786 | 0.9900 | 0.9844 | 0.9815 |
| Skew. | 0.0602 | 0.1216 | 0.4174 | −0.1815 | 0.3393 | 0.0675 | −0.0894 | −0.0371 | 0.1135 | −0.1635 | −0.2553 |
| Kurt. | 16.1842 | 2.3216 | 3.5275 | 3.2331 | 2.9721 | 3.0825 | 3.2391 | 2.2708 | 3.0775 | 2.8654 | 2.7013 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | −0.0000 | −0.0000 | 0.0714 | 0.0235 | −0.0000 | 0.0000 | −0.0206 | 0.0630 | 0.0017 | 0.0000 |
| S.D. | 0.9995 | 0.9980 | 0.9968 | 0.9037 | 0.6426 | 0.9993 | 0.9993 | 0.7214 | 0.9914 | 0.9631 | 0.9770 |
| Skew. | 1.6233 | 0.3349 | 0.1880 | 0.3597 | 0.1379 | −0.0071 | −0.1302 | 0.0305 | −0.5653 | −0.3025 | 0.1189 |
| Kurt. | 24.1005 | 2.6193 | 2.6016 | 1.7330 | 2.4193 | 3.1353 | 3.2580 | 1.8670 | 1.7633 | 2.0233 | 1.8322 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | 0.0000 | −0.0000 | 0.0000 | −0.0000 | −0.0000 | 0.0000 | 0.0039 | −0.0699 | −0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9978 | 0.9967 | 0.9952 | 0.9951 | 0.9988 | 0.9992 | 0.9941 | 0.9940 | 0.9873 | 0.9535 |
| Skew. | 0.8915 | −0.1445 | 0.6005 | −0.1373 | 0.2840 | −0.0192 | 0.1068 | −0.1490 | 0.8422 | −0.0977 | −0.0559 |
| Kurt. | 11.9483 | 1.7597 | 3.1006 | 1.6416 | 1.5410 | 3.8114 | 3.9849 | 1.5875 | 2.8223 | 3.3404 | 2.4796 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | −0.0000 | −0.0377 | −0.0000 | −0.0147 | −0.0305 | 0.0000 | 0.0788 | 0.0000 | −0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9979 | 0.9944 | 0.9967 | 0.9957 | 0.9971 | 0.9987 | 0.9901 | 0.9720 | 0.9911 | 0.9839 |
| Skew. | −0.6686 | −0.0660 | 0.2905 | 0.1639 | 0.6487 | 0.0975 | −0.2945 | −0.6429 | 0.1928 | −0.3869 | −0.2257 |
| Kurt. | 15.8906 | 1.9401 | 2.1066 | 4.0923 | 2.5879 | 1.9680 | 2.3146 | 2.9047 | 3.9969 | 2.8052 | 1.7873 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | −0.0000 | −0.0000 | −0.0476 | −0.0000 | −0.0000 | −0.0000 | 0.0000 | −0.0000 | 0.0000 | −0.0467 |
| S.D. | 0.9996 | 0.9986 | 0.9979 | 0.9954 | 0.9974 | 0.9986 | 0.9989 | 0.9957 | 0.9959 | 0.9900 | 0.9907 |
| Skew. | −0.2723 | 0.2103 | 0.5290 | −0.4124 | −0.0197 | −0.0174 | 0.1601 | 0.5165 | −0.2090 | −0.2510 | −0.5360 |
| Kurt. | 9.3622 | 2.7239 | 2.2319 | 2.0677 | 2.3970 | 2.5383 | 3.2492 | 2.8399 | 5.2540 | 3.5172 | 3.1566 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | −0.0000 | −0.0000 | 0.0000 | −0.0000 | 0.0000 | −0.0000 | 0.0982 | 0.0447 | 0.0000 | −0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9985 | 0.9983 | 0.9984 | 0.9982 | 0.9973 | 0.9918 | 0.9944 | 0.9963 | 0.9910 | 0.9939 |
| Skew. | −0.9395 | 0.1781 | 0.3910 | −0.3031 | 0.4756 | 0.8630 | −0.8874 | −0.1844 | −0.0017 | 0.1653 | −0.2408 |
| Kurt. | 19.8401 | 2.3163 | 5.5330 | 3.9451 | 3.9408 | 3.7029 | 2.7775 | 1.6964 | 1.9866 | 2.4217 | 2.9588 |

Table 2.5: Summary statistics of raw and conditional one-day normalized returs for all of the 25 Nasdaq stocks from our sample and in size quintiles, from 1992 to 1996, where neural networks with a **higher degree of smoothing** were employed in the pattern recognition algorithm. The conditional returns are conditioned on the occurence of each of the technical patterns under consideration.

| Moment | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0001 | -0.0002 | -0.0000 | 0.0000 | 0.0000 | -0.0004 | -0.0005 | -0.0000 | -0.0000 | -0.0000 |
| S.D. | 0.9995 | 0.9846 | 0.9781 | 0.9869 | 0.9857 | 0.9850 | 0.9881 | 0.9765 | 0.9795 | 0.9794 | 0.9703 |
| Skew. | 0.0602 | 0.4281 | 0.3214 | -0.0405 | -0.0479 | 0.2189 | 0.2300 | 0.3221 | -0.3785 | -0.0805 | -0.0302 |
| Kurt. | 16.1842 | 2.7049 | 3.8352 | 3.6661 | 3.7415 | 2.8782 | 3.2339 | 3.0272 | 4.0120 | 3.0509 | 2.8017 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | 0.0000 | -0.0021 | -0.0000 | 0.0000 | 0.0000 | -0.0013 | -0.0251 | 0.0000 | 0.0000 | 0.0000 |
| S.D. | 0.9995 | 0.9795 | 0.9697 | 0.9697 | 0.9677 | 0.9932 | 0.9922 | 0.7766 | 0.9618 | 0.9767 | 0.9608 |
| Skew. | 1.6233 | 0.3184 | 0.7767 | 0.3609 | -0.5892 | 0.2189 | 0.1127 | 1.3023 | 0.5498 | 0.2267 | 0.3538 |
| Kurt. | 24.1005 | 3.0938 | 6.0847 | 1.9356 | 4.8120 | 2.9361 | 2.9324 | 3.6174 | 2.2201 | 2.4291 | 2.3655 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | -0.0000 | 0.0000 | 0.0009 | 0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | 0.0000 | -0.0000 |
| S.D. | 0.9996 | 0.9907 | 0.9822 | 0.9857 | 0.9847 | 0.9915 | 0.9955 | 0.9851 | 0.9818 | 0.9811 | 0.9535 |
| Skew. | 0.8915 | 0.1550 | 0.1718 | -0.3315 | 0.3670 | 0.3961 | 0.5849 | 0.6248 | -0.3629 | 0.1551 | 0.2347 |
| Kurt. | 11.9483 | 2.4011 | 3.8405 | 2.4073 | 3.0025 | 3.5110 | 3.3037 | 4.4198 | 3.1390 | 2.4790 | 2.1883 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0004 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0004 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| S.D. | 0.9996 | 0.9897 | 0.9881 | 0.9921 | 0.9889 | 0.9913 | 0.9841 | 0.9841 | 0.9869 | 0.9846 | 0.9756 |
| Skew. | -0.6686 | 0.5791 | 0.8203 | 0.3771 | 0.4965 | 0.1321 | -0.0420 | -0.0009 | -0.2792 | -0.2971 | -0.0736 |
| Kurt. | 15.8906 | 2.8983 | 3.2583 | 3.9748 | 3.2595 | 1.9657 | 2.6028 | 2.9717 | 2.8262 | 4.0483 | 2.3791 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0000 | 0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0000 |
| S.D. | 0.9996 | 0.9893 | 0.9876 | 0.9918 | 0.9935 | 0.9682 | 0.9892 | 0.9861 | 0.9873 | 0.9863 | 0.9874 |
| Skew. | -0.2723 | 0.4249 | 0.0348 | -0.0189 | -0.3024 | 0.0620 | 0.0634 | 0.3668 | -0.8362 | -0.3105 | -0.0655 |
| Kurt. | 9.3622 | 2.4950 | 3.6309 | 3.7051 | 3.1276 | 2.8707 | 4.6781 | 2.1853 | 5.3469 | 3.3050 | 2.6900 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | -0.0000 | -0.0000 | -0.0015 | 0.0000 | -0.0000 | -0.0000 | -0.0004 | 0.0000 | -0.0000 | -0.0000 | -0.0000 |
| S.D. | 0.9996 | 0.9730 | 0.9600 | 0.9904 | 0.9873 | 0.9428 | 0.8564 | 0.9787 | 0.9796 | 0.9821 | 0.9816 |
| Skew. | -0.9395 | 0.9614 | -0.1472 | -0.5031 | -0.3099 | -0.1827 | -0.5437 | 0.1966 | -0.1575 | 0.0211 | -0.3824 |
| Kurt. | 19.8401 | 3.2741 | 3.8748 | 4.5748 | 5.7258 | 2.1261 | 1.7074 | 2.3107 | 5.3577 | 2.5498 | 4.0561 |

Table 2.6: Summary statistics of one-day raw and conditional returns, the latter of which are conditioned on the occurence of each of the technical patterns under consideration, for all Nasdaq stocks from 1992 to 1996 and in size quintiles, where the definitions of HS, IHS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT patterns include the **breaking of the neckline condition**, and where a lower degree of smoothing is used.

| Moment | Raw | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0000 | 0.0000 | -0.0057 | -0.0103 | -0.0000 | -0.0062 | 0.2646 | -0.0134 | 0.0002 | -0.0120 |
| S.D. | 0.9995 | 0.9958 | 0.9844 | 0.9956 | 0.9871 | 0.9963 | 0.9908 | 0.9452 | 0.4360 | 0.9844 | 0.9815 |
| Skew. | 0.0602 | 0.0600 | 0.0842 | 0.3373 | 0.0387 | -0.0577 | -0.0893 | 1.1689 | 9.0572 | -0.1635 | -0.2553 |
| Kurt. | 16.1842 | 3.7593 | 2.8270 | 2.6352 | 2.4984 | 2.6518 | 2.8723 | 7.1029 | 86.7438 | 2.8654 | 2.7013 |
| Largest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0000 | -0.0000 | 0.0792 | -0.1971 | -0.0000 | -0.0000 | - | - | 0.0017 | 0.0000 |
| S.D. | 0.9995 | 0.9954 | 0.9927 | 0.9863 | 0.7490 | 0.9983 | 0.9985 | - | - | 0.9631 | 0.9770 |
| Skew. | 1.6233 | -0.7398 | 0.0153 | -0.2607 | 0.4408 | -0.2169 | 0.0287 | - | - | -0.3025 | 0.1189 |
| Kurt. | 24.1005 | 3.1904 | 2.9050 | 1.9648 | 3.6688 | 2.6937 | 3.2632 | - | - | 2.0233 | 1.8322 |
| 2nd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | -0.0000 | 0.0000 | 0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | 0 | -0.0279 | -0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9955 | 0.9941 | 0.9948 | 0.9942 | 0.9969 | 0.9980 | 0 | 0 | 0.9873 | 0.9535 |
| Skew. | 0.8915 | 1.0235 | 0.0678 | 0.4447 | -0.4727 | -0.2242 | -0.1282 | - | - | -0.0977 | -0.0559 |
| Kurt. | 11.9483 | 6.2544 | 2.1646 | 3.0521 | 2.6752 | 3.0778 | 2.3851 | - | - | 3.3404 | 2.4796 |
| 3rd Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0101 | 0.0000 | -0.0000 | - | -0.0093 | -0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9959 | 0.9232 | 0.9962 | 0.9949 | 0.9957 | 0.9972 | - | 0.0313 | 0.9911 | 0.9839 |
| Skew. | -0.6686 | -0.2628 | 0.4958 | 0.1807 | -0.1480 | 0.1967 | -0.1539 | - | 4.1224 | -0.3869 | -0.2257 |
| Kurt. | 15.8906 | 2.5248 | 1.9866 | 2.4798 | 1.9869 | 1.8687 | 2.8585 | - | 25.1060 | 2.8052 | 1.7873 |
| 4th Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | 0.0000 | 0.0000 | 0.0000 | -0.0528 | -0.0000 | -0.0000 | -0.0000 | -0.0000 | -0.0316 | 0.0000 | -0.0467 |
| S.D. | 0.9996 | 0.9972 | 0.9958 | 0.9946 | 0.9970 | 0.9961 | 0.9977 | 1.0000 | 0.0227 | 0.9900 | 0.9907 |
| Skew. | -0.2723 | -0.3171 | -0.0870 | 0.2808 | -0.1408 | -0.1548 | -0.1326 | 4.6949 | 0.0000 | -0.2510 | -0.5360 |
| Kurt. | 9.3622 | 4.1361 | 1.9882 | 1.8106 | 2.1514 | 3.1634 | 2.9650 | 23.0417 | 1.0000 | 3.5172 | 3.1566 |
| Smallest Quintile, 1992 to 1996 | | | | | | | | | | | |
| Mean | -0.0000 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | -0.0755 | 0.3813 | -0.0000 | -0.0000 | 0.0000 |
| S.D. | 0.9996 | 0.9974 | 0.9973 | 0.9981 | 0.9980 | 0.9956 | 0.9103 | 0.9137 | 1.0000 | 0.9910 | 0.9939 |
| Skew. | -0.9395 | 0.5020 | 0.0904 | 0.4828 | 0.3605 | 0.6016 | -0.2653 | -0.5807 | 4.0069 | 0.1653 | -0.2408 |
| Kurt. | 19.8401 | 3.0603 | 3.7947 | 3.0529 | 2.7932 | 1.9999 | 2.3047 | 1.3670 | 17.0556 | 2.4217 | 2.9588 |

Note that in all three cases the summary statistics vary considerably not only between the normalized one-day raw and post-pattern returns, but also among the post-pattern returns of different pattern types. For example, from Table 5 we can see that the values of mean, standard deviation, skewness, and kurtosis are 0.0000, 0.9995, 0.0602, and 16.1842 for the raw returns, −0.0004, 0.9881, 0.2300, and 3.2339 for the post-RBOT returns, and −0.0000, 0.9795, −0.3785, and 4.0120 for the post-BBOT returns. The extent of the variation is even more evident from Table 6, where the above statistics read 0.2646, 0.9452, 1.1689, and 7.1029 for post-BTOP returns, −0.0134, 0.4360, 9.0572, and 86.7438 for post-BBOT returns, and −0.0120, 0.9815, −0.2553, and 2.7013 for post-DBOT returns. These differences constitute a preliminary evidence that conditioning on technical patterns does affect the distribution of returns, a proposition that shall be more formally examined in the rest of this thesis.

### 2.4.3 Empirical results

This more formal study starts with the analysis of of the goodness-of-fit diagnostics for our sample of Nasdaq stocks from 1992 to 1996 and for each type of technical patterns considered. For each pattern, we first compute the percentage of conditional returns that falls within each of the 10 unconditional-return deciles. If conditioning on the pattern provides no information, the expected percentage falling in each decile is 10%. In other words, we consider the null hypothesis that, for a particular pattern, the proportion of post-pattern returns in decile $j$, denoted by $p_j$, equals 0.1, with the alternative that the null hypothesis is not true, and report the asymptotic z-statistics and their associated p-values. We then consider the null hypothesis that $p_i = p_j \forall i, j \in [1, 10]$, with the alternative that the null hypothesis is not true, and report the associated $\chi^2$ goodness-of-fit statistics Q. As before, we repeat this procedure for each of the three cases under consideration: Tables 7 to 9 refer to the case where the pattern recognition algorithm employs a lower degree of smoothing, the case where it is based on a higher degree of smoothing, and the case where where the lower degree of smoothing is coupled with the breaking of the neckline requirement, respectively.

Table 2.7: Goodness-of-fit diagnostics for the conditional one-day normalized returns, for a sample of 25 Nasdaq stocks from 1992 to 1996 (5 stocks per size-quintile), where neural networks with a **lower degree of smoothing** were employed in the pattern recognition algorithm. For each pattern, the percentage of conditional returns that falls within each of the 10 unconditional-return deciles is tabulated in the first row. If conditioning on the pattern provides no information, the expected percentage falling in each decile is 10%. Asymptotic z-statistics for this null hypothesis are tabulated in the second row, while the associated p-values are reported in the third row. The $\chi^2$ goodness-of-fit test statistics Q are reported in the last column.

| Pattern | | Decile | | | | | | | | | | Q |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
| HS | $\hat{\delta}_j$ | 15.5 | 9.1 | 7.1 | 8.7 | 6.3 | 14.9 | 5.9 | 8 | 9.9 | 14.7 | |
| | z | 13.755 | -2.256 | -7.254 | -3.273 | -9.332 | 12.251 | -10.394 | -5.042 | -0.310 | 11.853 | 692 |
| | p | 0.0000 | 0.0241 | 0.0000 | 0.0011 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.7569 | 0.0000 | |
| IHS | $\hat{\delta}_j$ | 10.4 | 13.5 | 8.7 | 7.5 | 13.4 | 10.5 | 6 | 4.7 | 12.4 | 12.8 | |
| | z | 0.778 | 6.983 | -2.493 | -4.919 | 6.701 | 2.076 | -7.852 | -10.390 | 4.671 | 5.460 | 312.4 |
| | p | 0.4363 | 0.0000 | 0.0127 | 0.0000 | 0.0000 | 0.0379 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | |
| TTOP | $\hat{\delta}_j$ | 15.1 | 6.6 | 7.8 | 4.1 | 11.2 | 17.2 | 6 | 7.6 | 11.5 | 13 | |
| | z | 9.347 | -6.302 | -4.075 | -10.816 | 2.245 | 13.200 | -7.445 | -4.376 | 2.727 | 5.495 | 496.9 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0248 | 0.0000 | 0.0000 | 0.0000 | 0.0064 | 0.0000 | |
| TBOT | $\hat{\delta}_j$ | 10.7 | 12.2 | 10.6 | 3.4 | 13.1 | 15.6 | 7.8 | 1.8 | 8.8 | 16 | |
| | z | 1.189 | 3.975 | 1.003 | -11.876 | 5.585 | 10.043 | -3.889 | -14.663 | -2.217 | 10.848 | 579.6 |
| | p | 0.2345 | 0.0001 | 0.3158 | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0266 | 0.0000 | |
| RTOP | $\hat{\delta}_j$ | 13.7 | 7.9 | 6.8 | 6.8 | 8.1 | 23.7 | 5.9 | 5.6 | 8.7 | 13 | |
| | z | 10.585 | -6.017 | -9.039 | -9.196 | -5.467 | 38.648 | -11.708 | -12.532 | -3.740 | 8.466 | 1996.1 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0002 | 0.0000 | |
| RBOT | $\hat{\delta}_j$ | 13.4 | 8.4 | 4.3 | 3.4 | 12.1 | 24.7 | 3.3 | 7.6 | 10.1 | 12.7 | |
| | z | 11.017 | -4.989 | -18.287 | -21.030 | 6.607 | 46.883 | -21.343 | -7.767 | 0.427 | 8.482 | 3377.3 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.6693 | 0.0000 | |
| BTOP | $\hat{\delta}_j$ | 13.7 | 16 | 4.7 | 1.3 | 6.3 | 18.8 | 5.9 | 0 | 16.7 | 16.6 | |
| | z | 4.811 | 7.849 | -6.920 | -11.393 | -4.811 | 11.562 | -5.401 | -13.166 | 8.777 | 8.693 | 696.9 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | |
| BBOT | $\hat{\delta}_j$ | 13.8 | 14.3 | 6.8 | 3.6 | 7.7 | 16.9 | 3.4 | 7.5 | 13.6 | 12.4 | |
| | z | 5.629 | 6.382 | -4.756 | -9.422 | -3.401 | 10.219 | -9.723 | -3.702 | 5.253 | 3.522 | 403.2 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0007 | 0.0000 | 0.0000 | 0.0002 | 0.0000 | 0.0004 | |
| DTOP | $\hat{\delta}_j$ | 15.4 | 9.9 | 5.9 | 1.9 | 9.1 | 20.3 | 3.6 | 8 | 16.6 | 9.3 | |
| | z | 5.559 | -0.098 | -4.232 | -8.256 | -0.968 | 10.562 | -6.516 | -2.056 | 6.755 | -0.751 | 290.1 |
| | p | 0.0000 | 0.9220 | 0.0000 | 0.0000 | 0.3330 | 0.0000 | 0.0000 | 0.0398 | 0.0000 | 0.4529 | |
| DBOT | $\hat{\delta}_j$ | 14.5 | 11.8 | 3.8 | 11.6 | 2.8 | 13.5 | 9.2 | 7.7 | 11.3 | 14 | |
| | z | 4.639 | 1.841 | -6.448 | 1.625 | -7.416 | 3.563 | -0.850 | -2.357 | 1.302 | 4.101 | 145.5 |
| | p | 0.0000 | 0.0657 | 0.0000 | 0.1041 | 0.0000 | 0.0004 | 0.3951 | 0.0184 | 0.1928 | 0.0000 | |

Table 2.8: Goodness-of-fit diagnostics for the conditional one-day normalized returns, for a sample of 25 Nasdaq stocks from 1992 to 1996 (5 stocks per size-quintile), where pattern recognition was done using a **higher degree of smoothing**. For each pattern, the percentage of conditional returns that falls within each of the 10 unconditional-return deciles is tabulated in the first row. If conditioning on the pattern provides no information, the expected percentage falling in each decile is 10%. Asymptotic z-statistics for this null hypothesis are tabulated in the second row, while the associated p-values are reported in the third row. The $\chi^2$ goodness-of-fit test statistics Q are reported in the last column.

| Pattern | | Decile 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Q |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HS | $\hat{\delta}_j$ | 12 | 13.2 | 8.8 | 7 | 8.2 | 14 | 4.7 | 8.2 | 10.9 | 13 | |
| | z | 1.799 | 2.893 | -1.118 | -2.699 | -1.605 | 3.622 | -4.886 | -1.605 | 0.827 | 2.771 | 63.5851 |
| | p | 0.0720 | 0.0038 | 0.2634 | 0.0070 | 0.1086 | 0.0003 | 0.0000 | 0.1086 | 0.4085 | 0.0056 | |
| IHS | $\hat{\delta}_j$ | 10.2 | 9.4 | 15.2 | 4.5 | 9.1 | 15.4 | 2.2 | 17.3 | 5.1 | 11.6 | |
| | z | 0.177 | -0.414 | 3.875 | -4.111 | -0.710 | 4.023 | -5.886 | 5.502 | -3.668 | 1.213 | 115.7795 |
| | p | 0.8591 | 0.6788 | 0.0001 | 0.0000 | 0.4778 | 0.0001 | 0.0000 | 0.0000 | 0.0002 | 0.2252 | |
| TTOP | $\hat{\delta}_j$ | 10.8 | 11.6 | 7.9 | 7.2 | 7.3 | 18.8 | 6.1 | 7.4 | 10.7 | 12.3 | |
| | z | 0.769 | 1.648 | -2.088 | -2.857 | -2.747 | 8.902 | -3.956 | -2.638 | 0.659 | 2.308 | 117.8913 |
| | p | 0.4417 | 0.0993 | 0.0368 | 0.0043 | 0.0060 | 0.0000 | 0.0001 | 0.0084 | 0.5097 | 0.0210 | |
| TBOT | $\hat{\delta}_j$ | 13.5 | 8.6 | 6.5 | 5 | 9.4 | 22.9 | 7.9 | 6 | 7.3 | 12.9 | |
| | z | 3.356 | -1.340 | -3.402 | -4.891 | -0.538 | 12.519 | -2.027 | -3.860 | -2.600 | 2.783 | 215.1606 |
| | p | 0.0008 | 0.1802 | 0.0007 | 0.0000 | 0.5904 | 0.0000 | 0.0426 | 0.0001 | 0.0093 | 0.0054 | |
| RTOP | $\hat{\delta}_j$ | 15.6 | 8.7 | 5.6 | 5.8 | 8.4 | 21.8 | 6.1 | 6.8 | 8.1 | 13.1 | |
| | z | 5.509 | -1.264 | -4.312 | -4.086 | -1.603 | 11.604 | -3.861 | -3.183 | -1.829 | 3.025 | 217.7936 |
| | p | 0.0000 | 0.2061 | 0.0000 | 0.0000 | 0.1090 | 0.0000 | 0.0001 | 0.0015 | 0.0674 | 0.0025 | |
| RBOT | $\hat{\delta}_j$ | 14.1 | 8.8 | 2.7 | 11.1 | 8.7 | 20.6 | 8.4 | 5.3 | 8.5 | 11.8 | |
| | z | 4.929 | -1.416 | -8.865 | 1.343 | -1.600 | 12.837 | -1.968 | -5.646 | -1.784 | 2.1706 | 285.9087 |
| | p | 0.0000 | 0.1567 | 0.0000 | 0.1794 | 0.1096 | 0.0000 | 0.0491 | 0.0000 | 0.0744 | 0.0300 | |
| BTOP | $\hat{\delta}_j$ | 10.8 | 6.8 | 18.4 | 5.2 | 9.7 | 17.8 | 1.7 | 6.6 | 8.3 | 14.7 | |
| | z | 0.630 | -2.448 | 6.348 | -3.621 | -0.249 | 5.908 | -6.260 | -2.595 | -1.275 | 3.562 | 139.4990 |
| | p | 0.5284 | 0.0144 | 0.0000 | 0.0003 | 0.8032 | 0.0000 | 0.0000 | 0.0095 | 0.2022 | 0.0004 | |
| BBOT | $\hat{\delta}_j$ | 12 | 6.9 | 6.2 | 10.2 | 7.2 | 17.3 | 13.9 | 6 | 8.5 | 11.8 | |
| | z | 1.582 | -2.478 | -3.038 | 0.182 | -2.198 | 5.781 | 3.122 | -3.178 | -1.218 | 1.442 | 71.6067 |
| | p | 0.1137 | 0.0132 | 0.0024 | 0.8556 | 0.0280 | 0.0000 | 0.0018 | 0.0015 | 0.2233 | 0.1493 | |
| DTOP | $\hat{\delta}_j$ | 12.5 | 7.8 | 8.5 | 5.9 | 6.4 | 18.6 | 12.9 | 6.6 | 9.7 | 11 | |
| | z | 2.058 | -1.784 | -1.235 | -3.294 | -2.882 | 6.999 | 2.333 | -2.745 | -0.274 | 0.823 | 81.7288 |
| | p | 0.0395 | 0.0744 | 0.2168 | 0.0010 | 0.0040 | 0.0000 | 0.0197 | 0.0061 | 0.7837 | 0.4103 | |
| DBOT | $\hat{\delta}_j$ | 14.3 | 9.4 | 7 | 2.6 | 14.7 | 13 | 10.9 | 7.5 | 4.7 | 15.8 | |
| | z | 3.313 | -0.448 | -2.329 | -5.656 | 3.602 | 2.300 | 0.709 | -1.895 | -4.065 | 4.470 | 96.7024 |
| | p | 0.0009 | 0.6538 | 0.0199 | 0.0000 | 0.0003 | 0.0214 | 0.4784 | 0.0581 | 0.0000 | 0.0000 | |

Table 2.9: Goodness-of-fit diagnostics for the conditional one-day normalized returns, for a sample of 25 Nasdaq stocks from 1992 to 1996 (5 stocks per size-quintile), where the definitions of HS, IHS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT patterns include the **breaking of the neckline** condition, and where a lower degree of smoothing was used. For each pattern, the percentage of conditional returns that falls within each of the 10 unconditional-return deciles is tabulated in the first row. If conditioning on the pattern provides no information, the expected percentage falling in each decile is 10%. Asymptotic z-statistics for this null hypothesis are tabulated in the second row, while the associated p-values are reported in the third row. The $\chi^2$ goodness-of-fit test statistics Q are reported in last column.

| Pattern | | Decile 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Q |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HS | $\hat{\delta}_j$ | 11.9 | 6.9 | 9.4 | 9.2 | 12.4 | 15.9 | 3.8 | 7.7 | 8.7 | 14 | |
| | z | 3.435 | -5.542 | -0.991 | -1.490 | 4.245 | 10.604 | -10.966 | -4.046 | -2.363 | 7.113 | 332.1 |
| | p | 0.0006 | 0.0000 | 0.3216 | 0.1362 | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0181 | 0.0000 | |
| IHS | $\hat{\delta}_j$ | 10 | 11.1 | 12.4 | 5.2 | 8.9 | 15.3 | 6.3 | 4.6 | 13.8 | 12.4 | |
| | z | 0.053 | 1.628 | 3.580 | -7.077 | -1.673 | 7.857 | -5.501 | -7.977 | 5.606 | 3.505 | 240.9 |
| | p | 0.9581 | 0.1034 | 0.0003 | 0.0000 | 0.0942 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0005 | |
| TTOP | $\hat{\delta}_j$ | 12.4 | 15.6 | 5.9 | 5.4 | 8.4 | 18.7 | 3.9 | 2.8 | 14.1 | 12.9 | |
| | z | 4.147 | 9.493 | -6.937 | -7.915 | -2.699 | 14.774 | -10.327 | -12.348 | 6.950 | 4.864 | 697.2 |
| | p | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0070 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | |
| TBOT | $\hat{\delta}_j$ | 11.8 | 12.2 | 14.1 | 1.5 | 9.7 | 10.5 | 2.4 | 8.5 | 16.6 | 12.7 | |
| | z | 3.032 | 3.696 | 6.887 | -14.253 | -0.558 | 0.838 | -12.658 | -2.553 | 11.009 | 4.561 | 524.9 |
| | p | 0.0024 | 0.0002 | 0.0000 | 0.0000 | 0.5765 | 0.4022 | 0.0000 | 0.0107 | 0.0000 | 0.0000 | |
| RTOP | $\hat{\delta}_j$ | 15 | 9.8 | 5.7 | 6.2 | 8.5 | 16.1 | 5.3 | 10.5 | 9.2 | 13.7 | |
| | z | 9.324 | -0.309 | -7.980 | -7.088 | -2.807 | 11.406 | -8.872 | 0.880 | -1.558 | 7.005 | 422.9 |
| | p | 0.0000 | 0.7571 | 0.0000 | 0.0000 | 0.0050 | 0.0000 | 0.0000 | 0.3788 | 0.1192 | 0.0000 | |
| RBOT | $\hat{\delta}_j$ | 13 | 9.6 | 9.5 | 3.6 | 6.1 | 19.1 | 12.1 | 4.1 | 9.9 | 13 | |
| | z | 6.573 | -0.866 | -1.070 | -14.012 | -8.611 | 19.922 | 4.535 | -12.942 | -0.153 | 6.624 | 850.0 |
| | p | 0.0000 | 0.3864 | 0.2846 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.8785 | 0.0000 | |
| BTOP | $\hat{\delta}_j$ | 0 | 24.7 | 0 | 0 | 28.2 | 1.2 | 0 | 0 | 27.1 | 18.8 | |
| | z | -3.073 | 4.519 | -3.073 | -3.073 | 5.604 | -2.712 | -3.073 | -3.073 | 5.242 | 2.712 | 127.1 |
| | p | 0.0021 | 0.0000 | 0.0021 | 0.0021 | 0.0000 | 0.0067 | 0.0021 | 0.0021 | 0.0000 | 0.0067 | |
| BBOT | $\hat{\delta}_j$ | 0 | 0 | 0 | 0 | 18.8 | 80.2 | 0 | 0 | 0 | 1 | |
| | z | -3.266 | -3.266 | -3.266 | -3.266 | 2.858 | 22.930 | -3.266 | -3.266 | -3.266 | -2.926 | 555.5 |
| | p | 0.0011 | 0.0011 | 0.0011 | 0.0011 | 0.0043 | 0.0000 | 0.0011 | 0.0011 | 0.0011 | 0.0034 | |
| DTOP | $\hat{\delta}_j$ | 15.4 | 9.9 | 5.9 | 1.9 | 9.1 | 20.3 | 3.6 | 8 | 16.6 | 9.3 | |
| | z | 5.559 | -0.098 | -4.232 | -8.256 | -0.968 | 10.562 | -6.516 | -2.056 | 6.755 | -0.751 | 290.1 |
| | p | 0.0000 | 0.9220 | 0.0000 | 0.0000 | 0.3330 | 0.0000 | 0.0000 | 0.0398 | 0.0000 | 0.4529 | |
| DBOT | $\hat{\delta}_j$ | 14.5 | 11.8 | 3.8 | 11.6 | 2.8 | 13.5 | 9.2 | 7.7 | 11.3 | 14 | |
| | z | 4.639 | 1.841 | -6.448 | 1.625 | -7.416 | 3.563 | -0.850 | -2.357 | 1.302 | 4.101 | 145.4 |
| | p | 0.0000 | 0.0657 | 0.0000 | 0.1041 | 0.0000 | 0.0004 | 0.3951 | 0.0184 | 0.1928 | 0.0000 | |

We note that, on average, the values of the Q statistic are the greatest for the case with the lower degree of smoothing, where they range form 145.5 to 3377.3 (Table 7), and the least for the case with the higher degree of smoothing, where they range from 63.6 to 285.9 (Table 8). The case pertaining to the lower degree of smoothing coupled with the inclusion of the breaking of the neckline condition into the pattern definition is, on average, in the middle, its Q values ranging from 127.1 to 850.0 (Table 9). Such large values of Q bring us to conclude that the relative frequencies of the post-pattern returns are significantly different from those of the raw returns for each of the ten technical patterns and in each of the three cases under consideration. Moreover, the magnitude of this significance is overwhelming, which is precisely the conclusion that Lo, Mamaysky, and Wang drew from their kernel regression based analysis.

We further observe that, as we move from Table 7 to Table 9 to Table 8, the frequency counts of most patterns decline, as do their Q values. This suggests that some of the differences observed in these tables may be explained by the differences in the power of the test due to different sample sizes. For example, since the case with the highest degree of smoothing has the lowest frequency counts of patterns, the corresponding test statistics are subject to greater sampling variation and lower power for those patterns, hence the lowest Q values. This explanation is plausible for the BTOP patters as well, even though the value of their Q statistic rises as we move from Table 9 to Table 8, since their corresponding frequency counts also rise. However, the above reasoning cannot be applied to understand the way TTOP and BBOT formations behave as we move from Table 7 to Table 9, where the Q values increase even though the frequency counts for these patterns decrease (in the instance of BBOT patterns dramatically so). This seems to indicate that including the breaking of the neckline condition in the definitions of TTOP and BBOT patterns has an important effect on their information content. Here we have found yet another aspect in which the triangle and the broadening formations behave similarly, highlighting, once again, the need for a future investigation of their relationship and of the type of nonlinearities that they model.

Tables 10 to 12 report the results of the Kolmogorov-Smirnov test of the equality of the post-pattern and unconditional return distributions for all the stocks from our sample, from 1992 to 1996. Table 10 refers to the case where the pattern recognition algorithm employs a lower degree of smoothing, Table 11 relates to the case where it employs a higher degree of smoothing, while Table 12 concerns the case where the lower degree of smoothing is coupled with the breaking of the neckline requirement. The following statistics are reported in each table: (1) $D_{m,n} = \sup_{-\infty<x<\infty}|F_m(x) - G_n(x)|$, where $F_m$ and $G_n$ are sample distribution functions calculated from $m$ observed values of the conditional returns and $n$ observed values of the unconditional returns, (2) $\gamma_{m,n} = \sqrt{\frac{mn}{m+n}}D_{m,n}$, which, under the null hypothesis that $F = G$, should be small, and (3) p-values with respect to the asymptotic distribution of the Kolmogorov-Smirnov test statistic given by $\gamma_{m,n}$. In each table, statistics are reported in three ways: (1) unconditional of volume, (2) conditioned on decreasing volume trend ('$\tau(\searrow)$'), and (3) conditioned on increasing volume trend ('$\tau(\nearrow)$').

Table 2.10: Kolmogorov-Smirnov test for the equality of distributions of conditional and unconditional one-day normalized returns for all the stocks and over the entire time frame of our sample (1992-1996), where neural networks with a **lower degree of smoothing** were employed in the pattern recognition algorithm. In the top horizontal portion of the table, the conditional distibution is conditioned on the occurence of one of the 10 technical patterns under consideration; in the second horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and increasing volume trend ($\tau(\nearrow)$); in the third horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and decreasing volume trend ($\tau(\searrow)$). In the bottom horizontal portion of the table, we test for the difference between the increasing and decreasing volume-trend distributions.

| Statistic | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|
| ks-stat | 0.0711 | 0.0730 | 0.1157 | 0.1030 | 0.0997 | 0.1193 | 0.1350 | 0.0894 | 0.1132 | 0.0777 |
| $\gamma$ | 4.8188 | 4.0278 | 6.0305 | 5.2381 | 7.4242 | 9.7332 | 5.1673 | 3.8087 | 3.4024 | 2.3600 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| ks-stat $\tau(\nearrow)$ | 0.0817 | 0.0642 | 0.1699 | 0.1463 | 0.1170 | 0.1073 | 0.1724 | 0.0851 | 0.1307 | 0.1215 |
| $\gamma$ $\tau(\nearrow)$ | 3.5496 | 2.2725 | 5.1551 | 4.3995 | 5.7962 | 5.8888 | 4.0581 | 2.2596 | 2.2760 | 1.6008 |
| p-value $\tau(\nearrow)$ | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0001 | 0.0108 |
| ks-stat $\tau(\searrow)$ | 0.0909 | 0.0905 | 0.0955 | 0.0867 | 0.0776 | 0.1389 | 0.0999 | 0.1156 | 0.1538 | 0.1405 |
| $\gamma$ $\tau(\searrow)$ | 4.2391 | 3.0964 | 3.4135 | 2.8972 | 4.0253 | 8.0652 | 2.4579 | 3.1723 | 2.7792 | 3.0379 |
| p-value $\tau(\searrow)$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| ks-stat diff. | 0.0495 | 0.0670 | 0.1157 | 0.0927 | 0.0817 | 0.0754 | 0.1921 | 0.0742 | 0.1324 | 0.1819 |
| $\gamma$ diff. | 1.6454 | 1.9545 | 3.0248 | 2.4082 | 2.9179 | 2.8307 | 4.1121 | 1.7528 | 2.1836 | 2.3231 |
| p-value diff. | 0.0085 | 0.0062 | 0.0000 | 0.0002 | 0.0000 | 0.0000 | 0.0000 | 0.0301 | 0.0067 | 0.0003 |

Table 2.11: Kolmogorov-Smirnov test for the equality of the conditional and unconditional one-day return distributions for all the stocks and over the entire time frame of our sample, where pattern recognition was accomplished using a **higher degree of smoothing**. In the top horizontal portion of the table, the conditional distibution is conditioned on the occurence of one of the 10 technical patterns under consideration; in the second horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and increasing volume trend ($\tau(\nearrow)$); in the third horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and decreasing volume trend ($\tau(\searrow)$). In the bottom horizontal portion of the table, we test for the difference between the increasing and decreasing volume-trend distributions.

| Statistic | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|
| ks-stat | 0.0770 | 0.0623 | 0.0586 | 0.0942 | 0.1092 | 0.0972 | 0.1131 | 0.0850 | 0.0937 | 0.1001 |
| $\gamma$ | 2.0790 | 1.3887 | 1.7438 | 2.6955 | 3.1689 | 3.4307 | 2.5443 | 2.0000 | 2.2496 | 2.2815 |
| p-value | 0.0003 | 0.0405 | 0.0043 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0006 | 0.0001 | 0.0001 |
| ks-stat $\tau(\nearrow)$ | 0.1033 | 0.1222 | 0.1312 | 0.0817 | 0.0950 | 0.0870 | 0.0623 | 0.0930 | 0.1091 | 0.0906 |
| $\gamma\ \tau(\nearrow)$ | 1.7832 | 1.5596 | 2.0345 | 1.2883 | 1.6644 | 2.0314 | 0.9032 | 1.2805 | 1.5024 | 1.0608 |
| p-value $\tau(\nearrow)$ | 0.0032 | 0.0140 | 0.0004 | 0.0685 | 0.0072 | 0.0005 | 0.3776 | 0.0708 | 0.0201 | 0.2002 |
| ks-stat $\tau(\searrow)$ | 0.0653 | 0.0740 | 0.0826 | 0.0955 | 0.1001 | 0.1084 | 0.0773 | 0.1250 | 0.1140 | 0.0980 |
| $\gamma\ \tau(\searrow)$ | 1.1627 | 1.0549 | 1.6895 | 1.7915 | 2.0069 | 2.4589 | 1.0327 | 1.9975 | 1.7433 | 1.5627 |
| p-value $\tau(\searrow)$ | 0.1288 | 0.2073 | 0.0062 | 0.0030 | 0.0006 | 0.0000 | 0.2271 | 0.0006 | 0.0041 | 0.0140 |
| ks-stat diff. | 0.0896 | 0.1073 | 0.1119 | 0.0979 | 0.1151 | 0.0652 | 0.0990 | 0.1120 | 0.0689 | 0.0959 |
| $\gamma$ diff. | 1.1178 | 1.1181 | 1.3156 | 1.1620 | 1.4470 | 0.9311 | 1.1181 | 1.2260 | 0.7543 | 0.9423 |
| p-value diff. | 0.1559 | 0.2310 | 0.0384 | 0.1116 | 0.0169 | 0.1926 | 0.2817 | 0.1187 | 0.6824 | 0.3637 |

Table 2.12: Kolmogorov-Smirnov test for the equality of the conditional and unconditional one-day return distributions for all the stocks and over the entire time frame of our sample, where the definitions of HS, IHS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT patterns include the **breaking of the neckline** condition, and where a lower degree of smoothing is used. In the top horizontal portion of the table, the conditional distibution is conditioned on the occurence of one of the 10 technical patterns under consideration; in the second horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and increasing volume trend ($\tau(\nearrow)$); in the third horizontal portion of the table, the conditional distribution is conditioned on both the occurence of one of the 10 technical patterns and decreasing volume trend ($\tau(\searrow)$). In the bottom horizontal portion of the table, we test for the difference between the increasing and decreasing volume-trend distributions.

| Statistic | HS | IHS | TTOP | TBOT | RTOP | RBOT | BTOP | BBOT | DTOP | DBOT |
|---|---|---|---|---|---|---|---|---|---|---|
| ks-stat | 0.0714 | 0.0878 | 0.0929 | 0.1089 | 0.0836 | 0.1059 | 0.3289 | 0.4689 | 0.1132 | 0.0777 |
| $\gamma$ | 3.6067 | 3.7482 | 4.5078 | 5.1965 | 4.4072 | 6.3783 | 3.0269 | 4.5846 | 3.4024 | 2.3600 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | | | | | | | | | | |
| ks-stat $\tau(\nearrow)$ | 0.0921 | 0.1234 | 0.1589 | 0.1149 | 0.0796 | 0.0778 | 0.3836 | 0.4897 | 0.1307 | 0.1215 |
| $\gamma\ \tau(\nearrow)$ | 2.8896 | 3.3986 | 4.4056 | 3.2425 | 2.7186 | 3.0518 | 1.1507 | 3.1328 | 2.2760 | 1.6008 |
| p-value $\tau(\nearrow)$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.1065 | 0.0000 | 0.0001 | 0.0108 |
| | | | | | | | | | | |
| ks-stat $\tau(\searrow)$ | 0.0674 | 0.1642 | 0.0876 | 0.1197 | 0.0753 | 0.1049 | 0.4645 | 0.5100 | 0.1538 | 0.1405 |
| $\gamma\ \tau(\searrow)$ | 2.2737 | 4.1219 | 2.9298 | 3.7572 | 2.5939 | 4.1696 | 3.1816 | 2.4446 | 2.7792 | 3.0379 |
| p-value $\tau(\searrow)$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | | | | | | | | | | |
| ks-stat diff. | 0.0970 | 0.1998 | 0.1475 | 0.1077 | 0.0625 | 0.0870 | 0.5437 | 0.5907 | 0.1324 | 0.1819 |
| $\gamma$ diff. | 2.2774 | 4.3439 | 3.2199 | 2.3783 | 1.5373 | 2.2866 | 1.6251 | 3.7188 | 2.0687 | 2.2474 |
| p-value diff. | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0152 | 0.0000 | 0.0135 | 0.0000 | 0.0067 | 0.0003 |

Tables 10 to 12 show that all the patterns are statistically significant at the 5 percent level in all three cases under consideration. The values of the $\gamma$ statistic are, on average, the greatest for the case with the lower degree of smoothing, where they range from 2.3600 to 9.7332 (Table 10), and the least for the case with the higher degree of smoothing, where they range from 1.3887 to 3.4307 (Table 11). In the intermediate case of the lower degree of smoothing coupled with the inclusion of the breaking of the neckline condition in the definitions of first eight patterns, $\gamma$ ranges from 2.3600 to 6.3783. We observe that for all pattern types with the exception of BTOP, the drop in the value of $\gamma$ is coupled with the drop in the frequency count, which leads us to conclude that a lack of power of the Kolmogorov-Smirnov test due to small sample sizes might account for some of the reductions in statistical significance observed as we move across tables.

In the case of BTOP patterns, $\gamma$ and the frequency count move in the opposite directions, with $\gamma$ decreasing from 3.0269 to 2.5443 as we move from Table 12 to Table 11, and the frequency count increasing from 85 to 517. This suggests that the statistical significance of BTOP formations is especially significant in Table 12, since there the Kolmogorov-Smirnov test is likely to have lower power; hence, including the breaking of the neckline condition in the definitions of BTOP patterns may be important.

When we also condition on increasing volume trend, the statistical significance declines for most patterns in all three cases, the only exception being the TTOP pattern in Table 11. Conditioning on decreasing volume trend yields an increase in the significance of IHS and BTOP patterns in Table 12, as well as of DBOT patterns in Table 10. The difference between increasing and decreasing volume-trend conditional distributions is statistically significant for all the patterns in the lower degree of smoothing case, regardless of whether or not we require the patterns to break the neckline before we consider them complete. On the contrary, except for TTOP and RTOP patterns, the Kolmogorov-Smirnov test cannot distinguish between the decreasing and increasing volume-trend conditional distributions in the case with a higher degree of smoothing. This might suggest that conditioning on volume may be more important in very short-term, day to day trading, which is the situation corresponding to the lower degree of smoothing.

## 2.5 Monte Carlo Analysis

Finally, in Tables 13 to 15, we report the bootstrap percentiles for the Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions under the null hypothesis of equality, both for all the stocks from our sample from 1992 to 1996, and in size quintiles. Table 13 refers to the case where the pattern recognition algorithm employs a lower degree of smoothing, Table 14 relates to the case where it employs a higher degree of smoothing, while Table 15 concerns the case where the lower degree of smoothing is coupled with the breaking of the neckline requirement. For each of these three cases we scan the frequency counts reported in Tables 1 to 3 and search for their maximum and minimum values, which we denote $m_1$ and $m_2$, respectively.[14] We then perform 1000 Monte Carlo iterations in each of which we (1) construct a bootstrap sample of size $m_1$ and another of size

[14]We also require that both $m_1$ and $m_2$ are greater than one.

Table 2.13: Bootstrap percentiles for the Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions from 1992 to 1996, for all of the Nasdaq stocks from our sample and in size quintiles, under the null hypothesis of equality, and where neural networks with a **lower degree of smoothing** were employed in the pattern recognition algorithm.

| $m_1$ | $m_2$ | percentile | asym. | $D_{m_1,n}$ | $\gamma_{m_1,n}$ | $D_{m_2,n}$ | $\gamma_{m_2,n}$ |
|---|---|---|---|---|---|---|---|
| | | | All Stocks, 1992 to 1996 | | | | |
| 9217 | 939 | 0.0100 | 0.4410 | 0.0047 | 0.3799 | 0.0138 | 0.4139 |
| 9217 | 939 | 0.0500 | 0.5200 | 0.0055 | 0.4460 | 0.0160 | 0.4804 |
| 9217 | 939 | 0.1000 | 0.5710 | 0.0059 | 0.4852 | 0.0176 | 0.5297 |
| 9217 | 939 | 0.5000 | 0.8280 | 0.0088 | 0.7159 | 0.0262 | 0.7868 |
| 9217 | 939 | 0.9000 | 1.2240 | 0.0131 | 1.0660 | 0.0395 | 1.1860 |
| 9217 | 939 | 0.9500 | 1.3580 | 0.0145 | 1.1844 | 0.0437 | 1.3134 |
| 9217 | 939 | 0.9900 | 1.6280 | 0.0166 | 1.3548 | 0.0529 | 1.5890 |
| | | | Largest Quintile, 1992 to 1996 | | | | |
| 3016 | 89 | 0.0100 | 0.4410 | 0.0073 | 0.3086 | 0.0462 | 0.4311 |
| 3016 | 89 | 0.0500 | 0.5200 | 0.0090 | 0.3806 | 0.0541 | 0.5054 |
| 3016 | 89 | 0.1000 | 0.5710 | 0.0100 | 0.4220 | 0.0594 | 0.5544 |
| 3016 | 89 | 0.5000 | 0.8280 | 0.0145 | 0.6122 | 0.0860 | 0.8032 |
| 3016 | 89 | 0.9000 | 1.2240 | 0.0216 | 0.9092 | 0.1289 | 1.2036 |
| 3016 | 89 | 0.9500 | 1.3580 | 0.0240 | 1.0114 | 0.1397 | 1.3043 |
| 3016 | 89 | 0.9900 | 1.6280 | 0.0298 | 1.2554 | 0.1722 | 1.6082 |
| | | | 2nd Quintile, 1992 to 1996 | | | | |
| 2357 | 159 | 0.0100 | 0.4410 | 0.0088 | 0.3461 | 0.0346 | 0.4293 |
| 2357 | 159 | 0.0500 | 0.5200 | 0.0104 | 0.4120 | 0.0400 | 0.4963 |
| 2357 | 159 | 0.1000 | 0.5710 | 0.0115 | 0.4530 | 0.0434 | 0.5376 |
| x2357 | 159 | 0.5000 | 0.8280 | 0.0166 | 0.6556 | 0.0646 | 0.8010 |
| 2357 | 159 | 0.9000 | 1.2240 | 0.0243 | 0.9605 | 0.0933 | 1.1561 |
| 2357 | 159 | 0.9500 | 1.3580 | 0.0273 | 1.0771 | 0.1049 | 1.3001 |
| 2357 | 159 | 0.9900 | 1.6280 | 0.0313 | 1.2340 | 0.1282 | 1.5887 |
| | | | 3rd Quintile, 1992 to 1996 | | | | |
| 1494 | 126 | 0.0100 | 0.4410 | 0.0116 | 0.3914 | 0.0361 | 0.4004 |
| 1494 | 126 | 0.0500 | 0.5200 | 0.0136 | 0.4598 | 0.0441 | 0.4888 |
| 1494 | 126 | 0.1000 | 0.5710 | 0.0149 | 0.5018 | 0.0481 | 0.5335 |
| 1494 | 126 | 0.5000 | 0.8280 | 0.0208 | 0.7024 | 0.0700 | 0.7754 |
| 1494 | 126 | 0.9000 | 1.2240 | 0.0305 | 1.0297 | 0.1025 | 1.1361 |
| 1494 | 126 | 0.9500 | 1.3580 | 0.0336 | 1.1355 | 0.1142 | 1.2655 |
| 1494 | 126 | 0.9900 | 1.6280 | 0.0417 | 1.4081 | 0.1355 | 1.5009 |
| | | | 4th Quintile, 1992 to 1996 | | | | |
| 1749 | 203 | 0.0100 | 0.4410 | 0.0097 | 0.3483 | 0.0304 | 0.4248 |
| 1749 | 203 | 0.0500 | 0.5200 | 0.0119 | 0.4259 | 0.0346 | 0.4828 |
| 1749 | 203 | 0.1000 | 0.5710 | 0.0131 | 0.4705 | 0.0378 | 0.5275 |
| 1749 | 203 | 0.5000 | 0.8280 | 0.0195 | 0.7000 | 0.0564 | 0.7873 |
| 1749 | 203 | 0.9000 | 1.2240 | 0.0292 | 1.0469 | 0.0844 | 1.1778 |
| 1749 | 203 | 0.9500 | 1.3580 | 0.0330 | 1.1806 | 0.0942 | 1.3145 |
| 1749 | 203 | 0.9900 | 1.6280 | 0.0395 | 1.4163 | 0.1199 | 1.6736 |
| | | | Smallest Quintile, 1992 to 1996 | | | | |
| 1367 | 225 | 0.0100 | 0.4410 | 0.0113 | 0.3718 | 0.0280 | 0.4121 |
| 1367 | 225 | 0.0500 | 0.5200 | 0.0138 | 0.4562 | 0.0334 | 0.4908 |
| 1367 | 225 | 0.1000 | 0.5710 | 0.0153 | 0.5060 | 0.0369 | 0.5418 |
| 1367 | 225 | 0.5000 | 0.8280 | 0.0220 | 0.7272 | 0.0541 | 0.7958 |
| 1367 | 225 | 0.9000 | 1.2240 | 0.0333 | 1.1005 | 0.0806 | 1.1840 |
| 1367 | 225 | 0.9500 | 1.3580 | 0.0373 | 1.2307 | 0.0901 | 1.3248 |
| 1367 | 225 | 0.9900 | 1.6280 | 0.0465 | 1.5363 | 0.1116 | 1.6405 |

$m_2$ by resampling, with replacement, the one-day normalized returns, and (2) compute the Kolmogorov-Smirnov test statistic against the entire sample of one-day normalized returns. We also report the percentiles of the asymptotic distribution, for comparison.

These tables reveal that although the bootstrap distribution of the Kolmogorov-Smirnov statistic is, overall, close to its asymptotic distribution across size quintiles, degrees of smoothing, and for a wide range of sample sizes, there are some important differences among

Table 2.14: Bootstrap percentiles for the Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions from 1992 to 1996, for all of the Nasdaq stocks from our sample, and in size quintiles, under the null hypothesis of equality, and where pattern recognition was done using a **higher degree of smoothing**.

| $m_1$ | $m_2$ | percentile | asym. | $D_{m_1,n}$ | $\gamma_{m_1,n}$ | $D_{m_2,n}$ | $\gamma_{m_2,n}$ |
|---|---|---|---|---|---|---|---|
| All Stocks, 1992 to 1996 | | | | | | | |
| 1314 | 508 | 0.0100 | 0.4410 | 0.0120 | 0.4225 | 0.0186 | 0.4145 |
| 1314 | 508 | 0.0500 | 0.5200 | 0.0143 | 0.5043 | 0.0225 | 0.5012 |
| 1314 | 508 | 0.1000 | 0.5710 | 0.0157 | 0.5531 | 0.0247 | 0.5509 |
| 1314 | 508 | 0.5000 | 0.8280 | 0.0228 | 0.8046 | 0.0360 | 0.8024 |
| 1314 | 508 | 0.9000 | 1.2240 | 0.0335 | 1.1826 | 0.0530 | 1.1814 |
| 1314 | 508 | 0.9500 | 1.3580 | 0.0369 | 1.3017 | 0.0580 | 1.2933 |
| 1314 | 508 | 0.9900 | 1.6280 | 0.0439 | 1.5505 | 0.0730 | 1.6288 |
| Largest Quintile, 1992 to 1996 | | | | | | | |
| 383 | 11 | 0.0100 | 0.4410 | 0.0217 | 0.4065 | 0.1247 | 0.4132 |
| 383 | 11 | 0.0500 | 0.5200 | 0.0249 | 0.4677 | 0.1406 | 0.4658 |
| 383 | 11 | 0.1000 | 0.5710 | 0.0283 | 0.5302 | 0.1551 | 0.5139 |
| 383 | 11 | 0.5000 | 0.8280 | 0.0408 | 0.7646 | 0.2338 | 0.7745 |
| 383 | 11 | 0.9000 | 1.2240 | 0.0620 | 1.1635 | 0.3507 | 1.1617 |
| 383 | 11 | 0.9500 | 1.3580 | 0.0699 | 1.3099 | 0.3879 | 1.2850 |
| 383 | 11 | 0.9900 | 1.6280 | 0.0812 | 1.5234 | 0.4607 | 1.5261 |
| 2nd Quintile, 1992 to 1996 | | | | | | | |
| 442 | 108 | 0.0100 | 0.4410 | 0.0205 | 0.4120 | 0.0404 | 0.4149 |
| 442 | 108 | 0.0500 | 0.5200 | 0.0243 | 0.4890 | 0.0481 | 0.4937 |
| 442 | 108 | 0.1000 | 0.5710 | 0.0264 | 0.5302 | 0.0536 | 0.5501 |
| 442 | 108 | 0.5000 | 0.8280 | 0.0381 | 0.7658 | 0.0758 | 0.7788 |
| 442 | 108 | 0.9000 | 1.2240 | 0.0577 | 1.1585 | 0.1155 | 1.1866 |
| 442 | 108 | 0.9500 | 1.3580 | 0.0655 | 1.3145 | 0.1299 | 1.3348 |
| 442 | 108 | 0.9900 | 1.6280 | 0.0763 | 1.5321 | 0.1563 | 1.6060 |
| 3rd Quintile, 1992 to 1996 | | | | | | | |
| 286 | 84 | 0.0100 | 0.4410 | 0.0259 | 0.4252 | 0.0473 | 0.4302 |
| 286 | 84 | 0.0500 | 0.5200 | 0.0304 | 0.4988 | 0.0555 | 0.5044 |
| 286 | 84 | 0.1000 | 0.5710 | 0.0321 | 0.5272 | 0.0624 | 0.5673 |
| 286 | 84 | 0.5000 | 0.8280 | 0.0484 | 0.7947 | 0.0891 | 0.8094 |
| 286 | 84 | 0.9000 | 1.2240 | 0.0716 | 1.1768 | 0.1339 | 1.2163 |
| 286 | 84 | 0.9500 | 1.3580 | 0.0796 | 1.3073 | 0.1490 | 1.3540 |
| 286 | 84 | 0.9900 | 1.6280 | 0.0989 | 1.6257 | 0.1786 | 1.6232 |
| 4th Quintile, 1992 to 1996 | | | | | | | |
| 308 | 145 | 0.0100 | 0.4410 | 0.0257 | 0.4365 | 0.0356 | 0.4229 |
| 308 | 145 | 0.0500 | 0.5200 | 0.0292 | 0.4960 | 0.0422 | 0.5005 |
| 308 | 145 | 0.1000 | 0.5710 | 0.0318 | 0.5403 | 0.0468 | 0.5557 |
| 308 | 145 | 0.5000 | 0.8280 | 0.0465 | 0.7914 | 0.0680 | 0.8070 |
| 308 | 145 | 0.9000 | 1.2240 | 0.0695 | 1.1822 | 0.1002 | 1.1890 |
| 308 | 145 | 0.9500 | 1.3580 | 0.0774 | 1.3161 | 0.1109 | 1.3157 |
| 308 | 145 | 0.9900 | 1.6280 | 0.0929 | 1.5811 | 0.1315 | 1.5606 |
| Smallest Quintile, 1992 to 1996 | | | | | | | |
| 210 | 16 | 0.0100 | 0.4410 | 0.0296 | 0.4209 | 0.0985 | 0.3935 |
| 210 | 16 | 0.0500 | 0.5200 | 0.0344 | 0.4886 | 0.1205 | 0.4812 |
| 210 | 16 | 0.1000 | 0.5710 | 0.0382 | 0.5438 | 0.1319 | 0.5267 |
| 210 | 16 | 0.5000 | 0.8280 | 0.0565 | 0.8036 | 0.1978 | 0.7902 |
| 210 | 16 | 0.9000 | 1.2240 | 0.0846 | 1.2035 | 0.2931 | 1.1707 |
| 210 | 16 | 0.9500 | 1.3580 | 0.0932 | 1.3247 | 0.3290 | 1.3142 |
| 210 | 16 | 0.9900 | 1.6280 | 0.1115 | 1.5851 | 0.3990 | 1.5936 |

Table 2.15: Bootstrap percentiles for the Kolmogorov-Smirnov test of the equality of conditional and unconditional one-day return distributions from 1992 to 1996, for all of the Nasdaq stocks from our sample, and in size quintiles, under the null hypothesis of equality, where the definitions of HS, IHS, TTOP, TBOT, RTOP, RBOT, BTOP, and BBOT patterns include the **breaking of the neckline** condition, and where a lower degree of smoothing is used.

| $m_1$ | $m_2$ | percentile | asym. | $D_{m_1,n}$ | $\gamma_{m_1,n}$ | $D_{m_2,n}$ | $\gamma_{m_2,n}$ |
|---|---|---|---|---|---|---|---|
| | | | All Stocks, 1992 to 1996 | | | | |
| 4280 | 85 | 0.0100 | 0.4410 | 0.0067 | 0.4060 | 0.0464 | 0.4267 |
| 4280 | 85 | 0.0500 | 0.5200 | 0.0079 | 0.4744 | 0.0542 | 0.4985 |
| 4280 | 85 | 0.1000 | 0.5710 | 0.0086 | 0.5211 | 0.0600 | 0.5524 |
| 4280 | 85 | 0.5000 | 0.8280 | 0.0125 | 0.7517 | 0.0885 | 0.8145 |
| 4280 | 85 | 0.9000 | 1.2240 | 0.0186 | 1.1191 | 0.1354 | 1.2459 |
| 4280 | 85 | 0.9500 | 1.3580 | 0.0205 | 1.2348 | 0.1479 | 1.3615 |
| 4280 | 85 | 0.9900 | 1.6280 | 0.0243 | 1.4657 | 0.1744 | 1.6046 |
| | | | Largest Quintile, 1992 to 1996 | | | | |
| 1332 | 89 | 0.0100 | 0.4410 | 0.0119 | 0.3798 | 0.0437 | 0.4083 |
| 1332 | 89 | 0.0500 | 0.5200 | 0.0141 | 0.4487 | 0.0517 | 0.4828 |
| 1332 | 89 | 0.1000 | 0.5710 | 0.0155 | 0.4927 | 0.0569 | 0.5311 |
| 1332 | 89 | 0.5000 | 0.8280 | 0.0222 | 0.7085 | 0.0857 | 0.7999 |
| 1332 | 89 | 0.9000 | 1.2240 | 0.0334 | 1.0654 | 0.1321 | 1.2338 |
| 1332 | 89 | 0.9500 | 1.3580 | 0.0372 | 1.1853 | 0.1440 | 1.3442 |
| 1332 | 89 | 0.9900 | 1.6280 | 0.0453 | 1.4438 | 0.1664 | 1.5538 |
| | | | 2nd Quintile, 1992 to 1996 | | | | |
| 1011 | 26 | 0.0100 | 0.4410 | 0.0133 | 0.3839 | 0.0795 | 0.4043 |
| 1011 | 26 | 0.0500 | 0.5200 | 0.0161 | 0.4627 | 0.0951 | 0.4833 |
| 1011 | 26 | 0.1000 | 0.5710 | 0.0174 | 0.4997 | 0.1061 | 0.5394 |
| 1011 | 26 | 0.5000 | 0.8280 | 0.0259 | 0.7466 | 0.1605 | 0.8159 |
| 1011 | 26 | 0.9000 | 1.2240 | 0.0368 | 1.0585 | 0.2348 | 1.1937 |
| 1011 | 26 | 0.9500 | 1.3580 | 0.0421 | 1.2131 | 0.2590 | 1.3170 |
| 1011 | 26 | 0.9900 | 1.6280 | 0.0494 | 1.4227 | 0.3167 | 1.6101 |
| | | | 3rd Quintile, 1992 to 1996 | | | | |
| 715 | 47 | 0.0100 | 0.4410 | 0.0167 | 0.4161 | 0.0598 | 0.4080 |
| 715 | 47 | 0.0500 | 0.5200 | 0.0193 | 0.4805 | 0.0725 | 0.4945 |
| 715 | 47 | 0.1000 | 0.5710 | 0.0210 | 0.5244 | 0.0799 | 0.5453 |
| 715 | 47 | 0.5000 | 0.8280 | 0.0301 | 0.7504 | 0.1207 | 0.8233 |
| 715 | 47 | 0.9000 | 1.2240 | 0.0444 | 1.1071 | 0.1821 | 1.2422 |
| 715 | 47 | 0.9500 | 1.3580 | 0.0483 | 1.2052 | 0.2036 | 1.3891 |
| 715 | 47 | 0.9900 | 1.6280 | 0.0593 | 1.4789 | 0.2418 | 1.6498 |
| | | | 4th Quintile, 1992 to 1996 | | | | |
| 871 | 4 | 0.0100 | 0.4410 | 0.0141 | 0.3817 | 0.1981 | 0.3961 |
| 871 | 4 | 0.0500 | 0.5200 | 0.0169 | 0.4591 | 0.2319 | 0.4637 |
| 871 | 4 | 0.1000 | 0.5710 | 0.0184 | 0.5005 | 0.2511 | 0.5021 |
| 871 | 4 | 0.5000 | 0.8280 | 0.0270 | 0.7336 | 0.3774 | 0.7544 |
| 871 | 4 | 0.9000 | 1.2240 | 0.0414 | 1.1249 | 0.5694 | 1.1384 |
| 871 | 4 | 0.9500 | 1.3580 | 0.0459 | 1.2474 | 0.6274 | 1.2542 |
| 871 | 4 | 0.9900 | 1.6280 | 0.0536 | 1.4550 | 0.7263 | 1.4521 |
| | | | Smallest Quintile, 1992 to 1996 | | | | |
| 1052 | 19 | 0.0100 | 0.4410 | 0.0132 | 0.3905 | 0.0935 | 0.4069 |
| 1052 | 19 | 0.0500 | 0.5200 | 0.0155 | 0.4600 | 0.1105 | 0.4810 |
| 1052 | 19 | 0.1000 | 0.5710 | 0.0170 | 0.5040 | 0.1229 | 0.5347 |
| 1052 | 19 | 0.5000 | 0.8280 | 0.0248 | 0.7374 | 0.1781 | 0.7748 |
| 1052 | 19 | 0.9000 | 1.2240 | 0.0359 | 1.0653 | 0.2639 | 1.1484 |
| 1052 | 19 | 0.9500 | 1.3580 | 0.0394 | 1.1707 | 0.2877 | 1.2518 |
| 1052 | 19 | 0.9900 | 1.6280 | 0.0469 | 1.3926 | 0.3449 | 1.5009 |

the three cases under consideration. Namely, the bootstrap distribution of the Kolmogorov-Smirnov statistic is best approximated by its asymptotic counterpart in the case with a high degree of smoothing (Table 14), and worst approximated in the case with a low degree of smoothing (Table 13). This suggests that the neural network model characterized by a low degree of smoothing, which we have implemented because it was selected by professional technicians, suffers from overfitting. It probably just so happened that the technicians we interviewed were agressive short-term traders, who sought to exploit even the shortest-horizon technical patterns. Models with fewer nodes in the hidden layer may better capture the kind of nonlinearities that a broader range of technical analysts is looking for.

# Chapter 3

# Historical Overview

## 3.1 Objectives and Outline

Technical analysis can be fully appreciated only when a scientific investigation is accompanied by a historical one. Since technical analysis has its roots in trading and speculation, a historical study of the former should be paralleled by a historical study of the latter. With this in mind, we start with a brief overview of the main trends in the ancient Near Eastern trade from the Stone Age to the Iron Age, and summarize the evolution of the market economy of the ancient Mediterranean form its birth in the Iron Age to its climax in the Roman Empire. We then follow the commercial developments of Western Europe through the Middle Ages, Renaissance, and Industrial Revolution, before focusing our attention on the history of Wall Street, which is where the American version of technical analysis was born at the turn of the nineteenth century, and where it has continued to flourish to this day. To gain insight into the universal nature of technical analysis, we highlight the striking similarities between the American variation of the discipline and its older and arguably more progressive counterpart, the Japanese one. Finally, we conclude our historical section with a review of not only the most controversial, but also the oldest branch of technical analysis: financial astrology.

## 3.2 Commerce in the Ancient Near East

### 3.2.1 Neolithic

The earliest evidence of extensive trading activity dates back to the late pre-ceramic Neolithic - the period when the settled village life began and plants and animals were domesticated - and is found in the Jordan Valley. A distinction between local and long-distance trade is apparent, the former referring to the exchange of resources between the nomads and the villagers of the Jordan Valley settlements,[1] and the latter comprising of a network that connected the Jordan Valley with the Central Anatolian Plateau and the Zagros-Taurus arc.[2] [69, pp. 57-62]

During the ceramic phases of the Neolithic, the subsistence techniques (e.g. irrigation) were improved, and settled life became more established. The remnants of fully settled farming villages and small seasonal nomadic encampments have been found in lower and higher elevations of the Zagros Valley, respectively. The local movement of goods was in the form of the exchange of goods produced by the nomads, such as clarified butter, wool,

[1]The nomads would collect salt, bitumen, and sulfur from the shores of the Dead Sea, and exchange them for the villagers' farming products.

[2]The main object of the long-distance trade was Central Anatolian obsidian.

lambskins, and livestock, and the goods produced by the agricultural villages, such as grain, flour, fruit, vegetables, and craft items. Since there is no evidence of market structures in the Zagros during the sixth millennium B.C., it is believed that the exchange between the nomads and their parent villages took place along the blood-relationship lines. The long distance trade continued to grow slowly, with new materials being added to the trade network.[3] [69, pp. 62-67]

In the later ceramic Neolithic, around 5000 B.C., first large and specialized settlements came into being, including towns with temples and possibly markets, irrigation-farming villages lacking temples, dry-farming villages, pastoral camps in caves, and villages specializing in the production of a particular raw material or craft item.[4] In addition, nomadic encampments continued into this phase, with nomadism developing into a full-time occupation. The local trade declined – the local movement of goods was mainly in the form of redistribution of goods through the temple, rather than in the form of trade - but did not cease altogether. On the other hand, the long distance trade flourished like never before. The trade network, which grew to include an "impressive" variety of raw materials, extended 1500 miles from the major sites in northern Mesopotamia to the lapis mines in Afganistan.[5] [69]

[3]Alabaster, marble, cinnabar, wood, limestone, greenstone, and iron oxides are among the new materials that entered the long-distance trade.

[4]One such village was Tilki Tepe, which specialized in the preparation of obsidian for trade. For more examples, please see [69, p. 71].

[5]For a list of raw material used, please see [69, p. 70].

### 3.2.2 Bronze Age

The urbanization process culminated during the early Bronze Age. A myriad of small, disunited city-states emerged, only to be consolidated into empires ruled by a single king.[6] The first Mesopotamian empire was established by Sargon the Great in the twenty-fourth century B.C., with its capital at Agade.[7] All aspects of life in the empire, including the economic ones, revolved around religion, and the merchant, though free to pursue his private commercial activities, was primarily an agent of the temple [49, p. 49]. When later, starting with the Old Akkadian Dynasty and ending with the Third Dynasty of Ur, the political power became increasingly more concentrated in secular rather than religious institutions, the merchant extended his services to both the temple and the palace, never once abandoning his role as a private entrepreneur [49, p. 50]. Furthermore, the earliest written evidence of Mesopotamian overland trade dates back to the early Bronze Age. Sumerian epic literature, including the *Epic of Gilgamesh*, abounds in the allusions to the commercial reality of this period. [57, pp. 237-238]

After the fall of the last one of these empires, the Third Dynasty of Ur, at around 2000 B.C., the societal organization shifted back to a multitude of decentralized city-states, each ruled by its own king. However, the role of a king was largely ceremonial, and the city state was, in effect, run by the businessmen, who established trading colonies in Anatolia. [50, p. 23] Each colony was headed by a man appointed by the king, and inhabited by the representatives of private companies headquartered in the parent city-state. The latter,

[6] Please see [34, p. 67] and [49, p. 48].

[7] For a description of Sargon's expansionist efforts, please see [45, pp. 270-271].

who usually were male relatives of the principal businessmen, conducted business with the Anatolian regions. Though primarily an outlet for private profit-making opportunities, the colonies had some obligations toward the palace, such as selling the produce received as tax and produced in its sector, and supplying it with commodities it needed from abroad [54, p. 49]. The most important such colony was Karum Kanesh in Anatolia, a possession of the city-state of Ashur [50, p. 26].

In the ensuing Old Babylonian period, trade was in the hands of *takamaru* (singular *takamarum*), who acted as merchants, brokers, merchant bankers, money-lenders, or government agents. *Takamaru* dealt in slaves, foodstuffs, wool, timber, garments, textiles, grain, wine and ale, metals, building materials, and cattle and horses. Rather than going on the road themselves, they preferred to hire agents, loan them money, and send them on trading journeys; the code of conduct between the *takamarum* and his agents was spelled out by king Hammurabi.[8] [57, pp. 246-247] Furthermore, by this time the idea of interest was already present and surprisingly modern.[9]

During the following period, the late Bronze Age, the sociopolitical organization of the ancient Near East became more rigid. A number of larger regional units, governed by the 'great kings,' and subordinate local units, governed by the 'small kings,' emerged, greatly restricting both the overland trade and the sea trade [54, p. 67]. In effect, any commercial activity was limited to the adjacent regions, among which the political relations were formally

[8]Hammurabi (ca. 1795 - 1750 B.C.) is a celebrated Babylonian king and law-maker. Though his code of laws is not the earliest such document, it is the best preserved and the most important.

[9]A large number of tablets which pose textbook-like interest rates problems and provide their solutions date back to the second millennium B.C. [28, pp. 6-7].

established. Merchants belonged to the palace, and their private activities were minimal. [54, pp. 67-69]

### 3.2.3 Iron Age

In contrast to the large palace-towns of the Bronze Age, the settlements of the Iron Age were not palace-centered. They were small, diffuse, and numerous, and extended into the previously unpopulated far-away planes, hills, and deserts. This expansion was possible thanks to the technological improvements, such as the domesticated dromedary, an improved system for holding water, and the iron metallurgy. [54, pp. 70-71] Both the overland trade and the sea trade benefited enormously from the removal of political barriers and the related expansion of settlements and decentralization of power, as well as from the new technology. Merchants became freer, both in their business activities and in their physical movement. An Iron Age merchant was no longer an agent of the palace who engaged in private enterprise only as a side interest; now he was active mainly for his own profit and stimulated not by royal orders but by perceived market advantages. Moreover, he was no longer limited to the adjacent regions in his operations, but ventured far and away, often coming into close contact with the resident populations. [54, pp. 72-73]

## 3.3 Commerce in the Ancient Mediterranean

### 3.3.1 Hellenistic Age

By the middle of the first millennium B.C., a new type of economy was born in the ancient Mediterranean: the market-oriented one. Several factors contributed to its development. First, unlike the irrigation-based agriculture of the ancient Near East, the Mediterranean rainwater-based agriculture required little higher-level control, and allowed more individual initiative. Second, during the Iron Age, cheap iron tools became available to peasants and artisans, leading to a market expansion. Third, unlike the ancient Near East, which, due to its geographic location, had to rely on costly land transportation, the ancient Mediterranean had ready access to cheaper sea transportation, which was made even cheaper by the improvements in ship building brought about by the Iron Age. [18, pp. 90-91]

The Iron Age also gave rise to the improvements in warfare technique, thereby inducing great migrations of peoples at the end of the second millennium B.C. Among the migrating peoples were the Dorian tribes from the north, who completely destroyed the old Mycenaean-Minoan culture of Greece. During the settlement of Dorians in Greece, a highly uncentralized and divided regime emerged, consisting of a multitude of tribal groupings headed by the chiefs. These tribal groupings later broke up into nuclear families, giving rise to a household system of production. [18, pp. 97-98] What ensued was "the breakup of the solidarity based upon real or fictional kinship and of the common property of the kin," and the society became divided into "the possessors of land and a dependent or even landless peasantry" [18, p. 101]. The desire and the need for more land led to colonization, which lasted from the mid-eight to the mid-fifth century, and during which Greeks expanded to the western Mediterranean, the northern Aegean and the Black Sea, and Africa and Egypt [18, p. 102]. Different regions specialized in different products, and had to trade among themselves to obtain the ones they did not produce.[10] Significant trade was also done with Barbarian princes who had a taste luxuries. Soon, one could distinguish between two types of trade: *kapeleia*, or retail trade, which was land-borne, and *emporia*, or wholesale trade, which was sea-borne [27, p. 288].

The earliest evidence of coins comes from the Lydian capital of Sardis, and dates back to around 650 B.C. [18, p. 108]. By the fifth century B.C., the use of coinage in Greece, who borrowed the idea from the Lydians, became widespread, and the bank emerged as "the indispensable organ of trade" [27, p. 303]. The first banks were temples that accepted individual and state deposits, and lent them out at interest. As banks passed from temples into private hands, they came to serve the following main functions: (1) the accumulation of wealth in money, (2) the transfer of wealth by means of credit and checks, and (3) the allocation of funds for investment [18, p. 159]. Needless to say, along with the development of banks emerged the profession of banking.[11] By the fourth century B.C., banking and trade became tightly tied; it is precisely this union that "gave a sudden impulse to speculation," suggests Gustave Glotz, an authoritative historian of the ancient world [27, p. 306]. The development of speculative activities even caught the attention of Aristotle, who wrote about *chrematistichè*, or the art of getting rich [41, p. 9].

The rapid development of trade and coinage widened the gap between the rich and the

[10]For example, Egypt specialized in grain production, while the Agean specialized in manufactures and finer agricultural goods, such as oils and scents, wine, or wool cloth [18, p. 108].

[11]Please see [27, p. 304] for details regarding the first bankers.

poor, prompting the Athenian law-maker Solon (ca. 638 - 558 B.C.) and the Greek statesman and tyrant Pisistratus (ca. 607 - 528 B.C.) to introduce economic reforms favoring the poor in general, and the Athenian small farmer in particular. Soon, Athenian farmers started specializing in a particular crop (e.g. olives) and producing primarily for export, and the Athenian economy, "an economy of small farmers," became centered around domestic and international markets [18, p. 115]. Pisistratus instituted new festivals, such as the popular Great Duinysia, and undertook public constructions, such as the great temple to Olympian Zeus [18, p. 119]. Festivals, new constructions, demand for luxuries by the barbarian princes, and farm product exports, all required full-time services of professional artisans and merchants, leaving them with no time to grow their own food and hence dependent on the produce market for their livelihood [18, p. 120]. As Davisson and Harper explain, "for the first time in history, there appeared an urban class that made its living on the market, that needed to buy and sell in order to live"[12] [18, p. 120].

In the fourth and third centuries B.C., the Greek culture spread to southwestern Asia and northeastern Africa, including Mesopotamia, Egypt, and Italy. This process of Hellenization was at first peaceful, then characterized by Alexander of Macedonia's fierce conquests. As a result, the Mediterranean culture became more unified and the trade more open. [17, p. 80] More precisely, as the new Hellenistic market economy replaced the Athenian one, it "created a far larger area of trade in which the market replaced the port of trade and for

[12]However, the Athens' was not the first such market - that of the Lydian capital of Sardis [18, p. 120] and that of Corinth [24, p. 88] certainly preceded it. Nevertheless, as Davisson and Harper explain, "if this innovation did not first take place at Athens, it was first truly visible to us there, and it was through Athens that this innovation reached the rest of the Mediterranean world" [18, p. 121].

the first time really integrated the ancient Near East with the Greek world," write leading economic historians, Davisson and Harper [18, p. 151]. Circulation of money stimulated local trade by augmenting people's purchasing power, while further specialization of agricultural production gave rise to numerous interregional markets, such as those between the corn countries and the oil or wine countries. Commercial associations and partnerships were frequent, the organization of credit highly elaborate, and means of communication and transport significantly improved.[13] In such an environment the art of speculation reached new heights of creativity and sophistication, its most famous example being the wheat corner planned around the year 330 by Cleomenes.[14]

### 3.3.2 Roman Age

Further economic integration of the region came after the Roman conquest, which, as Davisson and Harper put it, "created an economic unity out of this vast region and endowed it with the institutions of the market economy" [18, p. 173]. Corporate organization, industrial insurance, and joint-stock companies became widespread, as did the practice of selling shares or *partes* to the public in order to raise capital [62, p. 3]. The economy peaked during the peaceful and prosperous Augustan Age (c. 43 B.C. - 18 A.D.), which enjoyed market-oriented agricultural production, an increase in the demand for luxuries, more regular issue of Roman coinage, extremely low interregional custom barriers, and blossoming international trade, particularly with the East.[15] The business class, also known as *equites*,

[13]For more detailed description of these developments, please see [27, pp. 362-371].
[14]For a description of this corner, please see [18, p. 151].
[15]Please see [18, pp. 202-206] or [70] for more details.

grew into "the most powerful force" of the Roman Age; in fact, as Robert Sobel, a prolific business historian points out, "commerce was so vital to Rome that its disruption was an important cause of her decline" [62, p. 3].

## 3.4 Commerce in Western Europe

### 3.4.1 Middle Ages

Following the disintegration of the Roman Empire in the fourth and fifth centuries, the European world sank deep into the turbulent and uncivilized Dark Ages. Society became organized in self-sufficient isolated little villages, also known as manors, and commercial activity, having become largely unnecessary, dwindled to a minimum [19, pp. 34-35]. The magnificence that was Roman culture disappeared, giving way to people who, in the words of Clive Day, a noted economic historian, were "coarse and ignorant, with little regard for personal cleanliness or for moral laws, and with practically no interests outside the narrow bounds of the little village in which they lived" [19, p. 36].

Then, in the latter part of the Middle Ages, after the year 1000, the situation changed dramatically. This reversal was due to the emergence of towns and the rise of a manufacturing class, whose livelihood of depended on the trade of wares for food with the surrounding countryside [19, p. 41]. It was trade and the closely related financial activity that pulled Europe out of the pangs of backwardness and inertia, and bestowed it with movement, cultural flourish, and economic prosperity. Merchants and bankers emerged as potent agents of change and driving forces of civilization that, in the words of Armando Sapori, a prominent scholar of Italian history, "[traced] for individuals and peoples of all times to come the only way that leads to a full realization of humanity" [58, p. 38].

Medieval merchants came in two varieties: the traveling and the sedentary ones. Among traveling traders, peddlers emerged as the least sophisticated kind. They usually traveled alone, carrying a wide variety of commodities on their back, on a horse, or in a wagon. Somewhat more sophisticated were the traveling merchants who dealt in raw materials, food, livestock, manufactures, and eastern imports. To protect their goods, they frequented the fairs traveling in armed groups rather than individually. More sophisticated still were sedentary merchants or city businessmen. As the name suggests, sedentary merchants were stationed at a city office or a warehouse, while their partners and agents traveled and handled business abroad. [31, pp. 162-164]

The merchant's close associate was the banker. Initially a simple money-changer, he frequented the fairs where he used to erect his *banca* (bench or table) and exchange local coins for the foreign ones. He later started handling deposits, lending deposited and his own money, and allowing depositors to withdraw money with prior notice. Depositors were awarded with interest or a share of any profit a banker made on their money. Bankers also began transferring money from one man's account to that of another. [31, p. 179] Furthermore, bills of exchange came into use as early as the thirteenth century; it was then that the Italian merchants started writing out the bills to each other instead of dealing in cash, having found them more convenient and less costly for handling large transactions

[53, p. 117]. Though in the early stages of capitalism banking was tightly connected with trade, in the fourteenth and fifteenth centuries the money business was becoming more and more purely financial and speculative [12, p. 328]. As commercial practices grew increasingly complex, the need for more advanced banking and accounting methods was becoming urgent. The adoption of Arabic numbers in the twelfth century was a big step forward, as it tremendously simplified all calculations. In the fourteenth century, double-entry bookkeeping was developed in Italy from where it spread to northern Europe. [13, p. 80]

Just like in the ancient civilizations, where the market activity flourished during religious festivals, with worshippers buying gifts to offer to their gods, so in the early medieval Europe much buying and selling took place in the churchyards after Sunday services [31, p. 169]. However, this practice did not last long, with the Church soon rising against the desecration of holy places. Consequently, markets had to be held weekdays on specifically designated marketplaces where carts could be parked, benches could be erected, and goods could be stored; town streets or town squares served this purpose well [13, p. 50]. "Thickly sprinkled over the country," individual markets served the towns in which they were located and a small area of the surrounding countryside [31, p. 168]. As towns grew larger, markets became twice or three times weekly events, with different hours of the market day reserved for different articles, and market halls were built to protect the goods from bad weather. Hence, with time, local markets were becoming better and better established and came to constitute "one of the most important elements of the basic urban framework." [12, p. 303]

Somewhat different in nature were the fairs, which, rather than serving local population, constituted periodic meeting places for distant traders. Held yearly or half-yearly in small sleepy towns, they lasted several days or even weeks, and dealt in wholesale rather than retail business. The most famous among the fairs were the Champagne ones, their golden age running from 1150 to 1300. The Champagne fairs played an important role in the development of credit, with people buying or borrowing at one fair and promising to pay or repay at a later one, and guaranteeing their promise with a *lettre de foire* (a fair letter). [31, p. 171]

A dominant force in the medieval mentality, religion penetrated deeply all levels of life, including the economic ones. The Church's position on commerce can be summed up by invoking two main economic doctrines that it preached: the doctrine of just price and the prohibition of usury. According to the former, it was wrong to sell a thing for more than it was worth, and, according to the latter, it was wrong to charge purely for the use of money loaned or advanced [13, p. 68]. Needless to say, these religious principles were difficult for merchants to uphold; even when ideologically they were close to the Church, they were simply humans, and, as such, vulnerable to the emotions of greed and fear, and constantly tempted to speculate.

Their speculative instincts thrived especially at the fairs; it was at the fairs, where "men strove continuously to maximize profits and business expanded without set limits in cut-throat economic competition," that capitalism started to take root [12, p. 311]. In its early stages, from 1300 to 1500, merchants learned to circumvent the dominant Christian ethic by resorting to many tricks which allowed them to "obey the letter of the canons but not their spirit" [12, p. 311]. For example, bills of exchange enabled medieval merchants to circumvent Church's prohibition of usury, since a bill purchased at a price lower than its face value was said to reflect the risk that it may not be honored when presented, rather than interest. With time, however, the Church gradually started to admit "that prices were linked to the laws of supply and demand; and with regard to interest they tempered the rigor of their doctrine with considerations based on the idea of risk, of injury to the creditor, and even of missed opportunities for profit" [12, p. 311].

### 3.4.2 Renaissance

By 1660, Europeans had discovered the New World and the route to the Far East around the Cape of Good Hope [48, p. 244]. The West was also penetrating into Russia and other Slavic lands. "To no other society in history had a whole world been opened for its exploitation," writes Frederick Nussbaum, a noted historian, in his book, *The Triumph of Science and Reason* [48, p. 245]. Naturally, such expansion had profound socioeconomic consequences. The discovery of the distant lands not only extended European markets overseas, but also incited national rivalries among the European nation-states, which had replaced the myriad of medieval provinces, dukedoms, and city-states at the beginning of the sixteenth century. Competition flourished as each nation-state sought to strenghten its economy and thereby consolidate its position at home and abroad.

Also ideologically, in 1660 Europe was in revolution; "at no time in its brief history as a society had any generation stood to the future with an orientation so distinct from that of its ancestors," explains Nussbaum [48, p. 1]. Whereas for two thousand years since the time of the ancient Greeks the purpose of natural science was to serve religion, in the seventeenth century its purpose became to master, by observation and measurement, the material world, which was assumed to be rational and distinct from the world of God. In fact, Renaissance is often referred to as the Age of Reason, and numerous great scientific and philosophical achievements are associated with it.[16] Two geniuses stand out in particular: Descartes and Newton. From *cogito, ergo sum* as his starting point, Descartes defined a Universe with man alone at its center. His 1637 text, *Discours sur la méthode de bien conduire la raison et chercher la vérité dans les sciences*, came to define the Cartesian system and the European mind for the centuries to come. No less momentous is Isaac Newton's *Philosophiae naturalis principia mathematica*, published in 1687 by the Royal Society. [48, p. 2]

Just as the scientific revolution of the Renaissance put emphasis on the individual, so the Protestant Reformation of the sixteenth century "supplied the merchant class with both a highly individualized moral responsibility outside the control of its clergy and with moral dogmas that emphasized exactly the thrift, industry, honesty, and promise keeping needed for capitalist institutions," explain Rosenberg and Birdzell in their book, *How the West Grew Rich* [53, p. 133]. In other words Protestantism, particularly of the Calvinistic sort, provided a moral system that was more suitable than the Catholic ethics for the rise of capitalism. In effect, Calvinism led to secularization of business in the sixteenth and seventeenth centuries, allowing it to grow independent from the intervention of religious authorities. As Rosenberg

[16]A summary of the great scientific achievements of this period can be found in [48, pp. 20-24].

and Birdzell put it, "religion was gradually transformed from a restraining influence upon capitalist development to a force that both sanctioned and supported mercantile capitalism by precisely the moral teachings required for the smooth running of the rising commercial system" [53, p. 132].

Further stimuli to the renaissance economy came form the unprecedented expansion in population and the associated urbanization process. The towns that prospered commercially grew in population. Soon, a changing pattern of urbanism emerged, with the old towns (Venice, Florence, Milan, Lisbon, Antwerp) declining and the new ones (Amsterdam, London, Paris) flourishing. Even the new European towns in the midst of wilderness – Lima and Mexico, Panama and Acapulco, New York and Boston - showed signs of urbanization during this period. [48, pp. 203-206] In fact, "*growth in trade* and *urbanization* are nearly equivalent expressions," according to Rosenberg and Birdzell [53, p. 80]. At the time when communications were slow, conducting business based on ties other than kinship was "inherently urban" in nature, since it required a community of knowledgeable and skilled individuals gathered in a single urban market [53, p. 139]. The existence of a single urban market led, in turn, to the development of trading institutions, such as, for example, the maritime insurance markets of Italy, Amsterdam, and London. The maritime insurance markets constituted a vehicle for separation of risk between the perils of the sea (storms, pirates) and the perils of the market (the cargo might not bring profit as high as expected), and, as such, encouraged trading activity. Moreover, as the volume of contracts and conflicts about them in trading centers grew, development of commercial law and commercial courts became imminent. [53]

Growth of towns put an enormous pressure on local markets. While in the Middle Ages it was customary for peasants to bring their produce to local markets to meet the local demand, in the Age of Renaissance it became customary for middlemen of all sorts to seek out peasants at their homes and buy up their produce for speculation and consumption [48, pp. 207-208]. Soon, permanent markets or exchanges replaced the periodic fares that flourished in the Middle Ages.[17] Among these new establishments, the Exchange of Amsterdam is best known.

As early as the mid-sixteenth century, there had been speculation in grain futures in Amsterdam, though the earliest list of price quotations from the Exchange dates back to 1585 [3, p. 74]. By the early seventeenth century, herring, spices, whale-oil, and grain were objects of speculative trading [3, p. 74]. Around the same time purely financial speculation in company shares began,[18] including transactions in options and futures; as Violet Barbour, the historian of Amsterdam capitalism, puts it, "one sees that without possessing actions or even a desire to acquire any, one can carry on a big business in them ... the seller, so to speak, sells nothing but wind and the buyer receives only wind" [3, pp. 78-79]. It is not only the sheer volume of speculation, but also the sophistication of its expertness, that stands out about the Bourse of Amsterdam. Speculative techniques were abstract,

[17]In his 1681 book entitled *Le Nouveau Négociant*, Samuel Ricard defines the exchange, also known as the bourse, as a "meeting-place of bankers, merchants and businessmen, exchange currency dealers and bankers' agents, brokers and other persons" [5, p. 97].

[18]The shares of great companies, the *Oost-Indische Compagnie* (the East India Company), founded in 1602, and the *West-Indische Compagnie* (the West India Company), founded in 1621, were among those quoted on the Exchange.

ingenious, and modern, indeed; a spectacular description is provided by Joseph de la Vega's 1688 text entitled *Confusion de Confusiones: Dialogos Curiosos entre un Philosopho Agudo, un Mercador Discreto y un Accionista Erudito, descriviendo el Negocio de las Acciones.* One of the most interesting examples of speculation, the so called tulip mania, occurred in the opulent city of Amsterdam in 1633-37.[19]

In addition to the exchanges, markets for trading bills of exchange emerged and came to dominate the renaissance economic landscape. Lesser-known merchants started depositing funds with better-known ones with the purpose of drawing on their better-known colleagues when paying by bills of exchange. Those who accumulated such assets realized that only a fraction of the funds needed to be available for withdraws, while the rest could be used to buy bills of exchange at a discount, that is, to lend money at interest. [53, p. 117] It did not take long for deposit banks to become a defining feature of the renaissance economy. The Bank of Amsterdam, founded in 1609, became a leader of European finance and credit [48, p. 215]. Whether they lowered the transaction costs, encouraged individuals to save and invest, or provided businessmen with the bank credit and increased the supply of capital available to the merchant class, all such banks fueled economic growth.[20]

The ever-growing renaissance economy necessitated an expansion in the money supply if it were to maintain itself. This was not a problem thanks to Europe's ability to take advantage of the riches of the New World. Much of the precious metals supply flowed through Spain to the rest of Western Europe, as Spain appropriated gold and silver from

[19] For detailed description of the tulip mania, please see [51].

[20] Please see [48, pp. 214-215] or [60, p. 8].

the Aztecs and the Incas, and exploited silver mines of Mexico and Peru [60, p. 6]. As a consequence of the inflow of precious metals and also due to the fact that kings of that time were often debasing the coins, the price level doubled or tripled throughout Western Europe. This rise in prices, which is known as *the price revolution*, was preceded by a hundred years of stationary or falling prices. Many economic historians believe that in the wake of the price revolution, production costs lagged behind selling prices, thereby making merchants and manufacturers better off.[21] In any event, the price revolution reduced the costs of exchanging goods and services. That facilitated the transition from barter to money economy, and led to redistribution of wealth in favor of the merchant class. Merchants and businessmen who, incidentally, were the class most inclined to save and invest, further increased their wealth by investing in great joint-stock companies.[22] [60, p. 7]

### 3.4.3 Industrial Revolution

Moving into the Industrial Revolution, the first thing that comes to mind is the shift from the artisan's shop to the factory system of production. This was made possible by a number of technological advances. The most important of the inventions was the steam engine, which not only revolutionized land and water transportation, but also, when applied to the printing press and together with the invention of the telegraph and the laying of the Atlantic cable in 1859, revolutionized communications [53, p. 151].

An inevitable consequence of the advances in transport and communications was the de-

[21]Though, as economic historians Scoville and La Force point out, this hypothesis has not been universally accepted [60, p. 7].

[22]In the second half of the seventeenth century, the stock companies became common.

cline of fairs. This decline was quickened by the growth of commercial integrity and honesty, and the improvements in commercial methods. In particular, introduction of standardization, the prearranged system to name and classify different kinds and qualities of goods, eliminated the need on the part of consumers to personally inspect the goods they were buying, allowing them to purchase based on a sample or a description. The decline of fairs was gradual, and it spread from west to east. [4, p. 51]

The fairs gave way to produce markets, exchanges, or bourses, as they are variously known. Unlike their predecessors, the produce markets were not limited to specified weeks of the year, but were open on a daily basis. Most of the transactions took place without the goods being physically present, and buyers and sellers, rather than haggling over the actual goods, engaged in abstract speculation of all kinds. Produce markets were usually specialized – for example, there were cotton, woolen, sugar, coal, iron, grain, rubber, and tea exchanges, to name a few – and the membership was restricted to a small group of people. [4, pp. 51-53]

The produce exchange supplied consumers with raw materials, rather than with finished manufactured articles. The latter had to be obtained through a myriad of intermediaries, such as the wholesale merchants, retail dealers, and commercial travelers. The last-named are of exceptional significance. Acting as "stimuli" or "nerves in the human body," they "[provoked] demand and [made] supply effective," thus providing "one of the most essential links in the ever-lengthening chain of middlemen which [stretched] between the producer and the consumer," writes a distinguished economic historian, Arthur Birnie [4, p. 53]. It is for this reason that Birnie assigns to them "a most important position in the modern commercial system" [4, p. 53]. Commercial travelers or 'bagmen,' came to existence in the early nineteenth century. Shrewd and energetic, they traveled between exchanges by a horse-drawn carriage, a railway, or a motorcar. These "great ambasadors of Parisian history," as Balzac once called them, were immortalized by the said author in his 1833 piece *L'Illustre Gaudissart* (*The Illustrious Gaudissart*).

While craftsmen's shops were a common feature of European towns since the Middle Ages, at the close of the eighteenth century a different kind of shop - the one kept by a dealer in commodities rather than by a producer - came to dominate the urban landscape of Western Europe. For example, there was in Paris, near Pont-Neuf, a retail shop called *Little Dunkirk*, which sold "French and foreign merchandize and every novelty produced by the arts" [4, p. 54]. These new modern retail shops started out as small general stores, but then, in the first half of the nineteenth century, became specialized. Later yet, in the second half of the nineteenth century, the small retail shop was overtaken by its giant counterparts – the large and the multiple shop. Both of these retail giants undermined the weekly market and the small shopkeeper. By the 1890s, the large shop of the universal provider type was present in all important towns of Europe; for example, there were *Whiteley's* and *Selfridge's* in London, and *Wertheim* and *Leonhard* in Berlin. [4, pp. 54-56]

Despite the enormous pressure exerted by the retail giants on the small shopkeeper, the latter did not disappear altogether as he had certain advantages. Namely, the small shopkeeper tended to pay special attention to the particular tastes and wants of his customers, and was usually located within their easy reach. Similarly, the weekly market, which was already in decline since the coming of the fair, experienced the pressure, but did not become extinct. Rather, it adapted to the new market conditions by specializing in goods that, being hard to standardize, required personal inspection by traders, such as fresh food-stuffs, fish, fruit, and vegetables. [4]

Moreover, as a result of the nineteenth century railway revolution and the accompanying advances in communications, the market for chief staples became worldwide in the following sense. First of all, railways and steamships meant that the produce exchange could obtain supplies from a wide geographical area, which, in the case of the chief staples like grain, rubber, and cotton, was the whole world. Secondly, coming of a telegraph smoothed out the price variation across the exchanges, as it enabled them to communicate with each other with minimum delay. As Birnie points out, this "establishment of world markets in the chief branches of trade is one of the most important commercial developments" of the nineteenth century. [4, p. 53]

Banks participated in the process of industrialization in a variety of ways. Most obviously, they served as intermediaries between borrowers and lenders, and provided short-term credit for working capital, thereby allowing industrialists to devote more of their own resources to fixed investment. In addition, banks supplied industrial enterprises with long-term loans and even bought their stocks; however, this was not their major function, since, given that they had to maintain a high degree of liquidity, banks could tie up only a small portion of their funds in long-term commitments. [9, p. 134]

More notably, banks provided the rapidly growing economy with an increased supply of the means of payment. Namely, in the eighteenth, nineteenth, and early twentieth centuries, banking institutions issuing money substitutes rose parallel with the rise of industry, first in England and Scotland, then on the continent of Western Europe and in North America [9]. This was significant for two main reasons. First of all, as an economy grows, its need for money also grows, and, in the case of rapidly industrializing economies, the money supply must grow much more rapidly than the total national product [9, p. 134]. Secondly, industrialization induced large shifts in the flow of resources from agriculture to secondary and tertiary sectors and from the declining industries, like handicrafts, to modern, mechanized ones. This transition required the expansion in the volume of money and money substitutes that would render the economy "more buoyant and responsive, more susceptible to changes in the pattern of resource deployment" [9, p. 136]. In fact, the increase in the means of payment that banks provided, "constituted one of their most important contributions to economic development," writes a leading economic historian, Rondo Cameron [9, p. 135].

However, the eighteenth century economic growth was not without difficulties - the overly restrictive commercial policy proved its major obstacle. Internal custom barriers or tariff walls burdened the domestic markets of continental European countries,[23] while the foreign trade was hampered by a nationalist commercial system known as *mercantilism*[24] [4, p. 61]. The change came about in the form of Adam Smith and his 1776 text, *The Wealth*

[23]Britain was the only European country that in the eighteenth century enjoyed free trade. That greatly contributed to her superior economic development in the later part of the eighteenth century. [4]

[24]The mercantalists believed that commerce was a kind of a war between nations where one could benefit only at the expense of others. Strong supporters of the State intervention, they held that it was the duty of the government to direct economic activities so as to maximize the national wealth [4, p. 62].

*of Nations.* Adam Smith advocated international division of labor as opposed to national self-sufficiency, firmly held that a man only can live by finding out what other men want, and strongly opposed the State intervention.[25] Smith's thinking was in agreement with the individualism and optimism characteristic of the eighteenth century philosophy; this won him readier acceptance, thereby starting a movement towards greater commercial freedom and allowing the competitive spirit to thrive. [4, pp. 65-66] It was precisely this "substitution of competition for the mediaeval regulations" that Arnold Toynbee called the "essence" of the Industrial Revolution[26] [64, p. 11].

### 3.4.4 General trends in the evolution of commerce from the Middle Ages to the nineteenth century

To summarize, the evolution of European commerce from the Middle Ages through the Industrial Age is characterized by three general tendencies: expansion, specialization, and integration [4, p. 57].

**Expansion** refers to the gradual widening of the market for staple commodities, from local to provincial, from provincial to national, and from national to international. While in the Middle Ages the international trade was synonymous with the luxuries, by the nineteenth century it grew to cater to both rich and poor, encompassing all sorts of articles of popular consumption. [4, p. 57]

[25] Smith's doctrine of *laisser-faire* is well-known.

[26] Arnold Toynbee formulated the classic statement of the industrial revolution in a series of lectures given in 1880-1881, which remain influential to this day.

**Specialization** was a two-fold process. First of all, it manifested itself in the division between industry and commerce. While in the later Middle Ages the craftsman sold the goods he himself had made, by the nineteenth century, the merchant and the producer were clearly separate individuals. Secondly, there was specialization within commerce itself, as seen in the sharp differentiation between wholesale and retail trade. Until the nineteenth century, the line between the two types of trade was blurred, and the same merchant might have engaged in both simultaneously. Thereafter, however, the specialized exchange replaced the fair, the specialized shop replaced the general store, and, as Birnie puts it, a "great army of specialized commercial functionaries, brokers, commission agents, commercial travelers, etc., each of whom [devoted] himself exclusively to one particular branch of the great work of buying and selling goods," came to existence. [4, p. 59]

**Integration** came later in time, as a reaction to excessive specialization. It called for the reunion of commercial functions separated in the course of the few preceding centuries. Integration manifested itself in: (1) the establishment of large shops of the universal provider type, (2) the invasion of the manufacturing process by retail traders (as when the Parisian grocer Potin opened factories for the production of jam, biscuits, soap, and chocolate that he later sold through his multiple shop system), and (3) the manufacturers playing an increasingly larger role in the marketing of their goods. [4, p. 59]

# 3.5 History of Wall Street

## 3.5.1 Origins of the Street

The first European settlement of New York dates back to 1621, when the Dutch colonists established the colony of New Netherlands with New Amsterdam as its capital [14, p. 10]. It was the Dutch who first laid out Wall Street. Namely, soon after settling down, they put up a brush fence along where Wall Street would shortly run, to keep hogs and goats in the city and to discourage the attacks by the Native Americans [29, p. 10]. The "practical and unpretentious" town of New Amsterdam was blessed with "the largest and finest harbor of North Atlantic" [29, p. 28]. Thanks to the Dutch emphasis on fair trade, New Amsterdam became the crossroads of commercial routes connecting Europe with the riches of the New World, and truly "the perfect spot for traders and merchants" [14, p. 10].

In contrast, England's North American colonies were mainly agricultural. The early colonists were predominantly farmers who were attracted to the New World by the abundance of good, cheap land; most of the time manufacturing, mining, and entrepreneurship were nothing more but their side interests. People tended to reinvest most of their surplus earnings into family enterprises, leaving just a little for speculation in land or English bonds.

Soon, the English settlers of New England began to "covet the little settlement located in the middle of so splendid a harbor" [29, p. 10]. In addition to the Native American tribes, the citizens of New Amsterdam now had to fight a new enemy: their British neighbors. Consequently, Peter Stuyvesant, the governor of New Netherlands, decided that the brush barrier was no longer adequate and that a proper wall was required to deter the British invaders. Hence, in 1653, he replaced the former with a 1,340-feet long and 12-feet high wooden construction. It did not take long for the street that ran along it to be named Wall Street, appropriately enough. [14]

The British indeed came in 1664, however not by land as Governor Stuyvesant had anticipated, but by sea. The Dutch surrendered, and the invasion ended peacefully. The terms of surrender were mild, and New Netherlands was able to continue doing business as usual. In particular, the British agreed that "all differences of contracts and bargains made before this day by any in this country, shall be determined according to the manner of the Dutch" [14, p. 11]. The *Articles of Capitulation* also stated that "any people may freely come from the Netherlands and plant in this country, and that Dutch vessels may freely come hither, and any of the Dutch may freely return home, or send any sort of merchandize home in vessels of their own country" [14, p. 11]. It was even the case that the elected Dutch officials were permitted to remain in office. Such agreement proved to be a highly intelligent move on the part of the British, suggests David Colbert, a noted historian, as it allowed them to benefit from "the strong currency, secure banks, reasonable interest rates, and fluid markets of the Netherlands, one of the most advanced economies in the world" [14, p. 11]. However, to honor the duke who financed their invasion, the British did require that the city be renamed New York immediately [14, p. 11].

As New York expanded, the wooden wall became useless and was torn down in 1698. Merchants moved to the Street in the early eighteenth century. Slaves, "those staples of seventeenth- and eighteenth-century commerce," were the main commodity of interest at this early time [29, p. 11]. Later, in 1752, New York's first formal market came into existence when a group of merchants organized a meeting place for dealings in slaves and corn meal. It was located at the foot of Broad Street and later in Fraunces Tavern, and held irregularly and infrequently [62, p. 15]. However, the colonial markets were not nearly as efficient as those of their mother countries, Britain and Holland, and many of the basic institutions were still lacking. Notably, the idea of an exchange "was slow in crossing the Atlantic" [26, p. 9].

### 3.5.2 Evolution of the New York Stock Exchange

Until the establishment of a strong federal government in the 1780s that followed the American Revolution, there were no full-time financial markets in North America. The reason is simple: there were few, if any, financial instruments to be traded. Then, in 1789, the Constitution came into effect, George Washington was inaugurated at the New York City Hall, and Alexander Hamilton was appointed the first Secretary of the Treasury. The last-named emerged as a most important figure of the country's financial scene. It was Hamilton who, in the words of John Steele Gordon, a noted market historian and author, argued that "one of the primary purposes in establishing a strong central government was to give people faith in the financial structure of the country and in the soundness of the currency and financial instruments of the government" [29, p. 11]. He managed to convince the Congress that the first natural step for the government in realizing this objective was refunding the debts it incurred during the Revolutionary War, and new federal bonds were issued for that purpose.

The significance of these new issues is twofold: first, they constituted a body of "rock-solid" securities that could be traded, and second, they greatly diminished the cloud of uncertainty in which the country had been enveloped [29, p. 12]. And, as Gordon puts it, "it is uncertainty - far more than disaster - that unnerves and weakens markets" [29, p. 12]. Not less importantly, continues Gordon, Hamilton's efforts established "a vital precedent for the future of Wall Street: that the United States Government would stand behind its financial instruments and not repudiate them for political reasons" [29, p. 12]. This precedent played a critical role in facilitating the establishment and growth of the country's financial markets.

Soon after the first American securities - the new federal bonds (or "stock" as they were then called) and state bonds - came into existence, the trading in them began [40, p. 28]. Initially, the trade was handled by commodity brokers who would meet on Wall Street or in its proximity; later, these brokers began to specialize in trading securities. When the weather was nice, their favorite meeting place was the shade of an old buttonwood tree at 68 Wall Street; in bad weather, they sought refuge in nearby coffee-houses.[27] "And thus, for all its present marble magnificence, the New York securities market began very humbly indeed in the heat and rain and dust of a village street," writes Meeker in his book, *The Work of the Stock Exchange* [40, p. 29].

Early in May of 1792, a group of the more important of these early brokers decided to get better organized. So, on the 17th of May, they gathered at Corre's Hotel, and signed the agreement that among other things stated:

[27]Buttonwood trees are also known as sycamores. Also, please see [40] for more details.

> We, the subscribers, brokers for the purchase and sale of public stocks, do hereby solemnly promise and pledge ourselves to each other that we will not buy or sell from this date, for any person whatsoever, any kind of public stock at a less rate than one-quarter of one per cent commission on the special value, and that we will give preference to each other in our negotiations. [62, pp. 20-21]

The Corre's Hotel Pact, in effect, established a guild of brokers. The first stock exchange agreement of any kind in this country, the Corre's Pact is taken to have "inaugurated" the New York stock market [40, p. 29].

Despite New York's efforts to improve its commercial effectiveness, it was Philadelphia that had supreme and more prestigious banks and that got most of the European business. Rivalry between the two cities was fierce indeed, with the Chestnut Streeters viewing the the Wall Streeters' actions "with suspicion and distrust" [62, p. 30]. The New York brokers, convinced that Philadelphia owned its financial supremacy to the fact that its were auctions better organized, decided to organize themselves on the model of Philadelphia. Twenty-eight prominent brokers formed the new Board of Brokers (later renamed New York Stock and Exchange Board), with the constitution that was almost an exact copy of the Philadelphia one [62, p. 30]. This first constitution dates back to March 8, 1817 [40, p. 30]. In 1863, the New York Stock and Exchange Board changed its name to the New York Stock Exchange.

Given the exclusivity of first the Board and then the Exchange, it is not surprising that much of the business took place outside, and not only among the nonmembers. The members themselves traded there after hours and in securities that were not listed on the Board. This outdoor exchange, also known as the curb market, was an "odd confabulation, whose roof was the sky, whose offices were in [brokers'] pockets, whose aspirations were boundless."[28] Some of these outdoor exchanges survived, others were absorbed by the Board, but most of them "just withered away when the financial climate, or even the weather, turned colder" [29, p. 14].

Then, in 1864, some of the curbers formed the Open Board of Brokers at 16-18 Broad Street. To organize their activities, they introduced rules for their innovative practices of admitting the public into the trading room and engaging in the continuous and the specialist types of trading. The curb and the Open Board became serious rivals to New York Stock Exchange. In fact, oftentimes the volume traded on the curb market would exceed greatly the volume traded on the floor of the New York Stock Exchange. On July 29, 1869, a mutually beneficial merger among the New York Stock Exchange, the Open Board, and the Government Bond Department took place.[29] As Wachtel points out, "this concentration and consolidation of securities trading in the NYSE paralleled the unification of capital in the industrial economy through the trust" [66, p. 149]. Despite this consolidation, new curb markets continued springing up from time to time. As Howard Wachtel, an economics professor, explains, this was due to the conservative attitude of the New York Stock Exchange towards new companies, which consequently could be traded only on the curb [66, p. 149]. The last surviving outdoor exchange, which at the time was known as "the Curb" and now is called the American Stock Exchange, was established in the 1920s [29, p. 14].

[28]Medberry, *Men and Mysteries of Wall Street*, pp. 130-131; quoted in [66, p. 147].
[29]The Government Bond Department was a specialized government bond exchange.

Together with the above developments, a new class of people – the *nouveau riche* or the newly affluent - emerged, imbuing New York with a culture of "prosperity, social conformity, piety, hypocrisy, and a profound sense of progress in human endeavor," as Gordon eloquently describes [29, p. 47]. It was also the culture that unreservedly embraced the gospel of wealth and considered finding a fortune a "sign of God's grace" [29, pp. 47-48]. By the 1820s, New York had become what Gordon calls "the greatest boom town the world had ever known" [29, p. 28], or, as Oliver W. Holmes puts it, "the tip of the tongue that laps up the cream of the commerce of a continent."[30]

### 3.5.3 Robber barons and investment bankers

The early Wall Street was a breeding ground for predatory practices, such as the use newspapers to influence public opinion and facilitate cornering operations, 'forward trading,' or 'wash sales'[31] [26, pp. 32-33]. Natural selection and the survival of the fittest became deeply rooted in the market reality, as did personal ruin and bankruptcy. The New York exchange, as well as other regional exchanges, came to constitute personal battlefields of the robber barons, "that undeniably American class of capitalists" [26, p. 36]. Though the robber barons came from a variety of socioeconomic backgrounds, they had two things in common: the lack of formal education and the gift for exploiting structural deficiencies of the

[30]Oliver Wendell Holmes, Sr., writing in 1835; quoted in [62, p. 27].

[31]In 'forward trading,' traders would buy a stock at an arranged price, and deliver cash for the transaction in a month or two. They hoped that, in the meantime, the price would rise, so that, upon completing the deal, they could quickly sell at a higher price and make instant profit. Such contracts were quite common during the stock exchange's early years, despite the fact that they were not legally binding [26, p. 32]. In 'wash sales,' traders would conspire to buy and then immediately sell stock to each other at a price lower or higher than the existing price, thereby artificially simulating a bull or a bear market and establishing the desired prices for themselves [26, p. 33], [62, pp. 30-31].

financial system. Cornelius Vanderbilt, Fisk, Gould, Drew, and Russell Sage, then John Rockefeller and Andrew Carnegie, are but a few prominent examples. They all amassed vast fortuned because of the structural deficiencies within the economy, and were indebted to their investment bankers, thanks to whom they were able to finance their ventures. [26]

The "promoter of the concept of Wall Street as trustee over the country's wealth," the investment banker "nudged aside the broker who had ruled the Street from its origins and became the most significant force on Wall Street in the last two decades of the [nineteenth] century," writes Wachtel [66, p. 136]. The investment banker was an underwriter; he purchased stocks and bonds from the companies, sold them in financial markets, and charged a considerable fee for his service. Investment bankers, such as J.P.Morgan, came to embody the spirit of the Industrial Revolution. In their hands, short-term money from a number of investors was being converted into long-term industrial investments, so indispensable for carrying on of the industrial developments.[32]

The main agents in the creation of corporate America, robber barons and their bankers took advantage of cornering operations, seizing smaller companies and creating the larger ones, in order to dominate the marketplace [26, pp. 68-69]. The tendency to consolidate that they established became "a tidal wave that swamped American industry" in the last quarter of the nineteenth century [26, p. 98]. Not only did the fittest survive, but now "they were colluding to ensure that they remained successful," explains Charles Geisst, a market historian [26, p. 98].

[32]For more details, please see [66].

### 3.5.4 Impact of technology

Like in Europe, in the U.S. technology contributed to the development of a national market. In 1866, the first permanent transatlantic telegraph cable was laid, establishing connection between London and Wall Street. Then, in 1867, a telegraph operator by the name of Edward A. Calahan invented the stock ticker, a printing device for stock prices that could be transmitted via telegraph. Before the invention of the stock ticker, messengers, also known as pad shovers, would literarily run from the exchange to the brokerage houses [66, p. 157]. A decade later, in 1878, the telephone, an invention of Alexander Graham Bell, was installed at the New York Stock Exchange. These three inventions - the telegraph, the stock ticker, and the telephone – "[pushed] the human brain's capacity to move information more quickly over space and to handle more of it," remarks Wachtel, thereby revolutionizing the way business was conducted on Wall Street [66, pp. 158-159].

### 3.5.5 The rise of technical analysis

At the turn of the nineteenth century "quite a cult of chartists mushroomed up who based their trading along technical lines" [63, p. 119]. The single most important figure in the rise of technical analysis on Wall Street was Charles H. Dow. After working as a newspaperman, a broker, and a floor trader on Wall Street, Dow became co-founder of the Dow, Jones and Company news service. On July 8, 1889, Dow, Jones, and Company first published the *Wall Street Journal*, with Dow as the editor. It was in his editorials that Dow proposed, at the turn of the nineteenth century, a highly influential theory of trends that later came to be known as the Dow Theory.[33] He is also celebrated for computing and publishing the Dow Jones industrial and railroad averages, which enabled traders to determine basic market trends. Such was his influence on the generations to come, that to this day he remains esteemed as the "father of technical analysis." What follows is an outline of some of Dow's most famous successors and their contributions to the field of technical analysis.

**Samuel Armstrong Nelson** Nelson is best known as the author of *The ABC of Stock Speculation* (1903), a book in which he compiled and organized Dow's key editorials, and referred to them as the Dow Theory. In addition, Nelson had many ideas of his own, which he presented in his other two books, *The ABC of Wall Street* and *The Consolidated Stock Exchange of New York.*

**William Peter Hamilton** In 1899, Hamilton, a journalist by profession, joined the *Wall Street Journal,* and soon became one of Dow's great followers. Hamilton not only organized, but also expanded Dow's ideas. As Harold Gartley, another great technician, points out, "the Dow Theory as generally understood [is] almost entirely the joint work of Dow and Hamilton" [25, p. 174]. In 1922, Hamilton published a book called *The Stock Market Barometer,* in which he combined Dow's ideas with his own and put forth a method of predicting a stock market.

**Robert Rhea** Rhea was a Dow historian rather than an innovator. His greatest contribution lies in his systematization of the wealth of wisdom left by Dow and Hamilton.

[33]Dow himself never called his observations a theory. In fact, it was only after his death that the term Dow's Theory was coined, by S.A. Nelson.

Rhea reduced the Dow Theory, as interpreted by Hamilton, to a set of axioms and theorems. It was Rhea's understanding that "the element of independent judgement or 'art' ... must accompany all Dow Theory interpretations" [25, p. 176]. He believed that Dow was successful not only because he possessed "the analytical power of a mathematician" and "the writing ability of a superior novelist," but also because he was blessed with "the intuitiveness of an artist" [56, p. 19]. Rhea is also famous for his article, *Stock Habits*, which appeared in the May 8, 1933 issue of *Barron's*. This article is the first discussion of the use of relative strength in stock market speculation [59, pp. 90-92]. He published three books: *Dow's Theory Applied to Business and Banking* (1938), *The Dow Theory* (1932), and *The Story of the Averages* (1932).

**Richard Russell** Russell is a recognized Dow theorist and historian. In 1960, he published *The Dow Theory Today*, a collection of twelve articles written between 1958 and 1960, in which he examined market developments by applying the Dow Theory to current and historical data. His market letter, *Dow Theory Letters*, which he began publishing in 1958, has a wide following.

**Richard W. Schabacker** Schabacker pioneered in the discovery of chart patterns in his highly influential books *Stock Market Theory and Practice* (1930), *Technical Analysis and Market Profits* (1932), and *Stock Market Profits* (1934).

**John Magee and Robert D. Edwards** Edwards and Magee used Schabacker's writings as a primary source in writing their *Technical Analysis of Stock Trends* (1948), a classic of the technical analysis literature, in which they not only systematized but also clarified and expanded Dow's and Schabacker's ideas.

**Harold M. Gartley** Gartley is credited for being the first to set down in writing the Wall Street's wisdom concerning trading volume and market breadth in his 1935 book, *Profits in the Stock Market.*

**Ralph Nelson Elliott** Using Rhea's writings on the Dow Theory and his own conviction that "the universe is ruled by law" where "all life and movement consists of vibrations" as his starting points, Elliott developed his wave principle of the stock market movement [55, pp. 53-59]. *Nature's Law - The Secret of the Universe*, published in 1946, is considered his final and definitive work on the principle.

**William D. Gann** Similar to Elliott, Gann believed in the "natural order existing for everything in the universe" [39, p. 3]. Convinced that "everything in existence [was] based on exact proportion and perfect relationship," he turned to the ancient sciences to discover how the stock market fit into nature's grand scheme[34] [32, p. 11]. Despite the esoteric nature of his theories, Gann is said to have had success rate on trades averaging to 80-90%, for which he became known as the "master trader" [39, pp. 2-3]. He wrote eight books, the best known of which are *Wall Street Selector* (1930), *45 Years in Wall Street* (1949), and *Truth of the Stock Tape* (1932).

**John J. Murphy** Murphy is a popular contemporary author on the subject. His *Intermarket Technical Analysis* (1991) pioneered a branch of technical analysis emphasiz-

[34]The above-mentioned ancient sciences include numerology, astronomical cycles, astrological interpretations, time cycles, Biblical symbology, and sacred geometry [67, p. 66]. In addition, Gann researched early Egyptian writings, and even traveled to India to gain access to the ancient pre-Hindu literature [32, p. 12].

ing interrelationships between various financial markets, while his *Technical Analysis of the Financial Markets*[35] (1999) is regarded as the standard reference in the field. *The Visual Investor* (1996), which applies charting principles to sector analysis, is his third book.

## 3.6 Comparative Study: Japanese vs. American Technical Analysis

During the seventeenth century, the Japanese castle town of Osaka grew into a great commercial center, and, due to its role as the national storehouse and a distributor of supplies, became known as the "kitchen of Japan" [46, p. 14]. By the late seventeenth century, the previously established informal rice exchange was institutionalized to become the Dojima Rice Exchange, located in downtown Osaka. The Exchange soon counted 1300 rice dealers. Up until 1710, trading was done in actual rice. The year 1710 saw the introduction of rice coupons, which, in effect, became "the first futures contracts ever traded" [46, p. 15]. It is at such early rice exchanges that the art of trading and speculation became more and more refined, eventually giving birth to Japanese technical analysis.

One of the greatest speculators of this time, and one of the fathers of Japanese technical analysis, was Munehisa Homma. Also known as the "god of the markets," Homma presented his ideas on technical analysis in his 1755 book entitled *San-en Kinsen Hiroku* (*The Fountain*

[35]Rev. ed. of: *Technical Analysis of the Futures Markets.* c1986.

*of Gold - The Three Monkey Record of Money*).[36] Parallels between Homma's wisdom and that of Charles Dow are striking. For example, Homma noticed that traders' emotions significantly influenced the price of rice, and concluded that "the psychological aspect of the market was critical to [one's] trading success" [47, p. 14]. He hence began "studying the emotions of the market" which, he believed, "could help in predicting prices" [47, p. 14]. Similarly, as Russell points out, Dow's "observations concerning the emotions of the crowd and the movements of stocks form an intricate part of the Theory" [56, p. 17]. Moreover, Homma described the rotation of Yang, or bullishness, and Yin, or bearishness. As Nison, the author of the "bible" of candle charting analysis, clarifies, "this [rotation] means that within each bull market, there is a bear market," and that "within each bear market, there is a bull market" [47, p. 15]. This is strikingly similar to the ideas Dow presented in his famous editorial *Swings within Swings*, almost a century and a half later. Homma also emphasized that "when all are bearish, there is cause for prices to rise," and that "when everyone is bearish, there is cause for the price to fall," which is practically equivalent to the contemporary theory of contrary opinion [47, p. 14]. He further advised that in order to "to learn about the market *ask the market* - only then can you become a detestable market demon," which sounds much like the *market discounts everything* principle of the Dow Theory [47, p. 16]. Finally, comments such as "volume has declined considerably" show that Homma paid attention not only to price, but also to volume, further revealing the level

[36] As Japanese technical analyst and author Hiroshi Okamoto points out, Japanese technicians of Homma's time rarely publicly disclosed their knowledge, but preferred to keep it a family secret. Consequently, written material concerning the early Japanese technical analysis is extremely rare, *The Fountain of Gold* being among the most treasured pieces [2, p. 12-13].

of sophistication of his technique [2, p. 13].

Given such remarkable similarities, it is important to consider "whether the analytical methods which developed separately in the U.S. and Japan turned out to be similar to each other because imaginative latitude is limited in this area, or whether the analytical method in one country developed first and then was disseminated to the other country," suggests Okamoto [2, p. 13]. Okamoto believes that the latter is true, Japan being the country of origin, and adds that the rice market in Osaka opened many years before the United States even won its independence in 1776 [2, p. 13]. Similarly, Nison finds it "amazing that before America was a nation, the Japanese were trading with contrarian opinion!" [47, p. 14]. Moreover, it has been argued that the Japanese version of technical analysis is not only older, but also more progressive that its American counterpart. For example, Nison suggests that the fact that "most of the West is still using bar charts," which are "one of the ancestors of the more evolved and productive candle charts," implies that "it is also using a less evolved form of charting than the Japanese are with candle charts"[37] [47, p. 18].

## 3.7 History of Financial Astrology

We will close our historical review with not only the most controversial, but also the oldest branch of technical analysis: financial astrology. Though often denounced as mere witchcraft, financial astrology has become undeniably a market factor, as more and more market participants are turning to stars to guide their investment decisions [67, p. 20]. Financial astrologers

[37]According to Nison, Japanese candle charts went through the following stages in their evolution: stopping charts, pole charts, bar charts, anchor charts, and, finally, candle charts [47, pp. 16-18].

believe that their craft is a tool for understanding market psychology. Henry Weingarten, a noted financial astrologer and author on the subject, describes it as "a mathematical psychology based on astronomy," capable of charting not only certain cosmic events, but also human emotions [67, p. 25]. As James Hyerczyk, an author on the subject of technical analysis, explains, "the planets' orbits, rulerships, groups of planets, and the sun and moon have an effect on the minds and actions of people," and therefore on the stock market [32, p. 19]. Financial astrologers hence study the natal horoscopes of markets and companies, as well as the positions of planets in the sky at any given time, and use them to chart and forecast the cycles and prices of stocks and commodities. However, they tend to use their craft in conjunction with conventional techniques, rather than in isolation. According to them, astrology is just one of the three "screens" or "layers" necessary for a successful investment strategy, the other two being fundamental analysis and technical analysis [67, p. 27].

Financial astrology has its roots in the earliest civilizations. In ancient Mesopotamia, recording market values of various commodities was an "old and continuous" custom.[38] Within this custom a prominent place belongs to the Babylonian astronomical diaries, which were recorded on cuneiform clay tablets for almost four centuries in the city of Babylon, and which are believed to have originated between -747 and -734, during the reign of Nabonassar[39] [61, p. 5]. Among other things, the diaries regularly charted market quotations of barley, dates, mustard/cuscuta, cress/cardamom, sesame, and wool, often revealing even the

[38]For example, Old Babylonian royal inscriptions listed "ideal" commodity prices, in order to give an impression of prosperity, while the Laws of Ešnunna and the Hittite Law Code both specified legal prices for various commodities. Other sources of commodity prices include the *Chronicle of Market Prices*, as well as literary texts such as the *Coronation Prayer of Assurbanipal* and the *Curse of Agade* [61, pp. 8-9].

[39]Although the earliest available diary dates back to -651 [61, p. 5].

smallest intraday fluctuations [61, p. 21]. Furthermore, Alice Slotsky, a historian of the ancient Near East, suggests that "the activities of the later diary writers were not limited to observation and record-keeping, but grew to encompass scientific forecasting" [61, p. 19]. In particular, the celestial omen corpus provides evidence of the attempts to forecast astrologically the cultivation, yield, and storage of various commodities, as well as the behavior of their market prices [61, pp. 25-29].

Another historical example of the application of financial astrology to commercial decision making is provided by *Memoria de tucte le mercantile* (1278), the oldest surviving Italian medieval commercial reference work.[40] In addition to being "a well rounded repertory of all things a merchant ought to know," this *Memoria* boasts a detailed astrological appendix [38, p. 38]. "Such a close connection of spices and stars does not occur in any other manual, and it certainly gives food for thought," writes Lopez, a great twentieth-century medievalist [38, p. 40]. While Lopez goes on to suggest that merchants made their purchasing decisions based on astrological forecasts, he concedes that it was not a common practice.

Among the contemporary financial astrologers, the most prominent place belongs to Arch Crawford and Bill Meridian [15, p. 109].

[40] *Memoria de tucte le mercantile* is believed to have been compiled by a Pisan merchant or notary in 1278 [38, p. 38].

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# Chapter 4

# Conclusion

In this thesis, we revisited the kernel regression based pattern recognition algorithm designed by Lo, Mamaysky, and Wang (2000) to extract nonlinear patterns from the noisy price data, and developed an analogous neural network based one. We argued that, given the natural flexibility of neural network models and the extent of parallel processing that they allow, our algorithm was a step forward in the automation of technical analysis. More importantly, following the approach proposed by Lo, Mamaysky, and Wang, we applied our neural network based model to examine empirically the ability of the patterns under consideration to add value to the investment process. We discovered overwhelming support for the validity of these indicators, just like Lo, Mamaysky, and Wang did. Moreover, we found this basic conclusion to remain valid across different levels of smoothing and insensitive to the nuances of pattern definitions present in the technical analysis literature. This confirms that Lo, Mamaysky, and Wang's results are not an artifact of their kernel regression model, and suggests that the kinds of nonlinearities that technical indicators are designed to capture constitute some underlying properties of the financial time series itself. In this thesis, we attempted to gain insight into the nature of these foundations by studying the relationships between patterns in sections 2.4.2 and 2.4.3, but hope to investigate this issue systematically in future research. Finally, we complemented our empirical analysis with a historical one, focusing on the origins of trading and speculation in general, and technical analysis in particular. Spanning several civilizations - from the most ancient to the modern ones - and several continents, our exposition highlighted the universal nature of these activities, revealing them as the most powerful driving forces of progress in human endeavor.

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