1 Technical Analysis and Random Walks

There are two kinds of security analysis. Fundamental analysis seeks to forecast each stock's return by studying the prospects for the company's business. Technical analysis attempts to forecast the return by searching for patterns in past stock prices.

Although a glance at any chart of past stock prices will often suggest such patterns, these could be no more than an optical illusion. Consider, for example, the following series of graphs. Figure 1.1 depicts the level of the Dow Jones Average during 1981. It appears to be characterized by typical short-term patterns. Yet when it is reconstructed in figure 1.2 as a chart of the weekly changes in the index, the symmetry disappears and is replaced by an apparently meaningless jumble.

The next two diagrams reverse the process. Figure 1.3 is a hypothetical series of random price changes. There neither is nor appears to be any pattern in figure 1.3. Yet when it is reconstructed in figure 1.4 as a chart of the levels of the counterfeit prices, the resulting graph acquires many of the characteristics of actual charts of the market, even to the "head and shoulders" pattern that is beloved by technical analysts.[1]

The moral of the story is this: Do not assume without questioning because there are regularities in price *levels* that

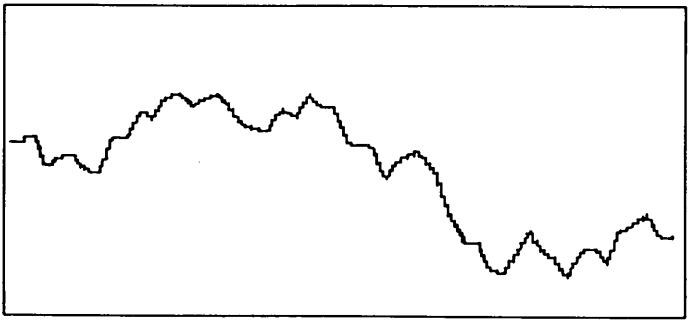

Figure 1.1
The weekly levels of the Dow Jones Average in 1981 appear to be characterized by regular patterns.

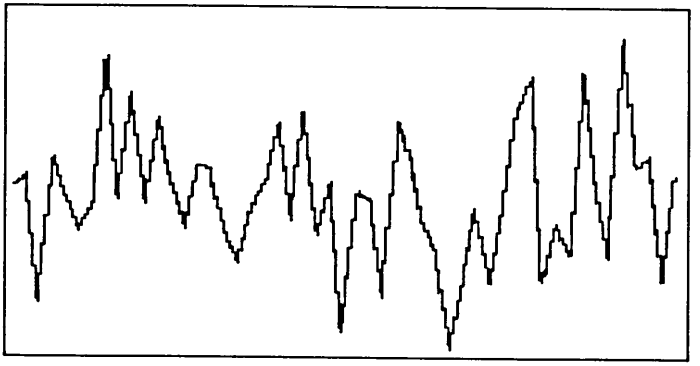

Figure 1.2
The changes in the Dow Jones do not appear to follow any pattern.

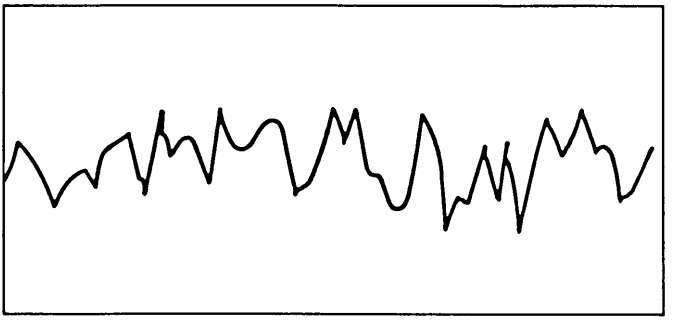

Figure 1.3
This series of random numbers looks like the changes in the Dow Jones Average.

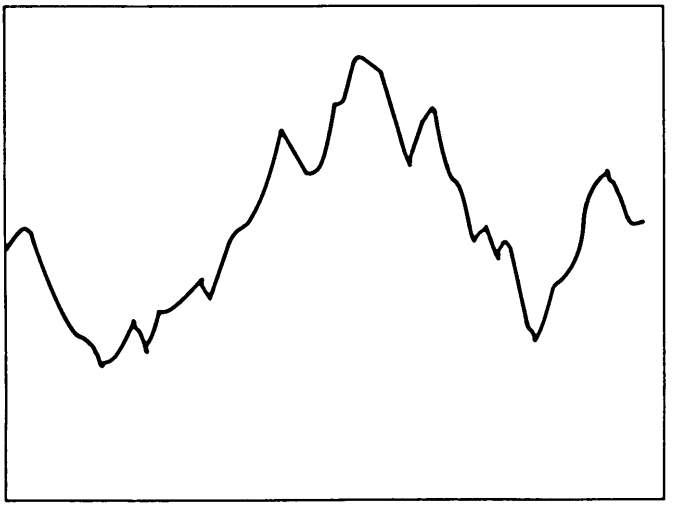

Figure 1.4
The cumulation of the series of random numbers looks like the level of the Dow Jones.

there must also be regularities in price *changes*. The charts that you have been studying may be no more than an accumulation of random price changes.

Some Statistical Tests of Price Patterns

As a simple check on this possibility, it is helpful to look at the extent to which price rises or falls tend to persist. In order to do this, we classify each price change as positive, zero, or negative and then count the runs of successive changes of the same sign. Thus the series + + + − 0 − would consist of four such runs. If there is a tendency for such changes to persist, the average length of run will be longer and the total number of runs will be less than if the same price changes were distributed randomly. A classic test of this kind examined the daily price changes of the thirty Dow Jones stocks over a period of about five years ending in 1962.[2] The first entry in table 1.1 shows the average actual number of runs for each stock. The second entry shows the average number of runs that we should expect if the plus days and minus days were mixed in a wholly random fashion. These figures suggest a very slight tendency for runs to persist, but it is negligible for most practical purposes. Indeed the remaining entries in table 1.1 show that when the exercise is repeated for four-, nine-, and sixteen-day changes, even this slight dependence disappears.

This simple runs test considered only the direction of price changes and took no account of their size. An alternative is to draw for each stock a scatter diagram like figure 1.5. The horizontal axis represents the daily change in the stock price, and the vertical axis represents the change on the following day. Each cross depicts the price movement of a hypothetical stock on a particular pair of days. If price changes are random, the crosses will be scattered incoherently over the chart as in figure 1.5. On the other hand, if the crosses tend to cluster along a straight line, we should have evidence of regularities in price behavior that might be worth exploiting.

Table 1.1
Actual and expected number of runs of consecutive price changes in the same direction for each of the Dow Jones stocks

	1-day change		4-day change		9-day change		16-day change	
	Actual	Expected	Actual	Expected	Actual	Expected	Actual	Expected
Average number of runs	735	760	176	176	75	75	42	42

Source: E. F. Fama, "The Behavior of Stock Market Prices," *Journal of Business* 38 (January 1965):34–105.

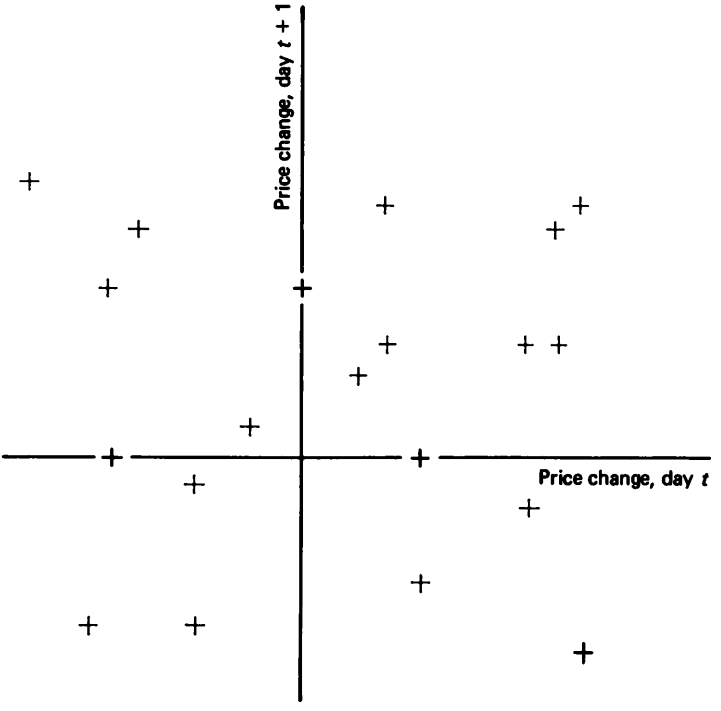

Figure 1.5
Each cross in this scatter diagram shows the price changes of a hypothetical stock in two successive periods.

Table 1.2
Average correlation between successive price changes for each of the Dow Jones stocks

	1-day changes	4-day changes	9-day changes	16-day changes
Correlation coefficient	0.03	−0.04	−0.05	0.01

Source: E. F. Fama, "The Behavior of Stock Market Prices," *Journal of Business* 38 (January 1965):34–105.

The correlation between successive price changes is a measure of the extent to which the crosses in our diagram tend to cluster along a straight line. The correlation may take any value between minus one and plus one. If there is no relationship between successive changes, the correlation will be zero. If each price change tends to be repeated, the correlation will be positive; if each change tends to be reversed, it will be negative.

Table 1.2 summarizes the correlation between the successive price changes of each of the Dow Jones stocks over the five years to 1962.[3] In each case the correlation is extremely close to zero, which is exactly what we should expect if price changes are random.

The runs test and the correlation analysis represent only a small sample of a vast number of such statistical studies of randomness in the price changes of common stocks. These studies have examined price changes over periods varying from a day to a month; they have extended back to 1875 and forward to the present day; they have looked for relationships between successive price changes and lagged price changes; they have covered stocks of both large and small firms. In no case was the random walk approximation seriously offended.

If you remain unconvinced that we are dealing with a fairly pervasive phenomenon, then look at table 1.3. It shows

the correlation between successive monthly changes in the stock prices of thirty-six countries.[4] Technical analysts around the world seem to share a common affliction.

Two Common Technical Rules

These statistical analyses of price changes suggest that there are no worthwhile simple patterns in price fluctuations. But technical analysts could plead with some justification that statistical tests are not powerful enough to detect the complex relationships with which they are concerned. For example, suppose that there exists a group of professional investors who are better equipped than their fellows to assess a stock's worth. If their time is free and there are no costs to dealing, they will compete to buy or sell stock whenever the price differs from the estimated value. As a result, if the competition between professional investors is sufficiently intense, the stock price will never deviate from the estimated value.

In practice, the time of professional investors is not free and dealing costs are not zero. Therefore most investment managers are likely to require some minimum degree of misvaluation before they will act. In this case the stock price would be free to wander within limits. It would not fall below the estimated value by more than the professional investor's costs and it would not rise above the estimated value by more than those costs. Of course the professional investor's opinion of the stock's worth and, therefore, his buying and selling limits are also likely to change from time to time. In these circumstances prices would meander between periodically shifting barriers, as in figure 1.6.[5]

Notice that major price movements in figure 1.6 occur only when professionals change their expectations and adjust their buying and selling limits. Therefore, if investors really behave in this way, it might be profitable to use the following trading rule:

Table 1.3
Correlation between successive monthly changes of stock market indexes

Country	Correlation coefficient
Argentina	0.12
Australia	0.12
Austria	0.20
Belgium	−0.20
Brazil	0.08
Canada	−0.03
Ceylon	−0.15
Chile	0.05
Colombia	−0.11
Denmark	−0.23
Egypt	0.02
Finland	0.09
France	−0.19
Germany	0.17
Greece	0.25
Hong Kong	0.12
India	0.11
Ireland	0.40
Israel	−0.03
Italy	0.02
Japan	0.04
Lebanon	0.00
Mexico	0.00
Netherlands	0.01
New Zealand	−0.05
Norway	−0.24
Peru	−0.34
Philippines	0.01
Portugal	0.09
South Africa	0.11
Spain	−0.15

Table 1.3 (continued)

Country	Correlation coefficient
Sweden	−0.10
Switzerland	−0.09
United Kingdom	0.04
United States	−0.02
Venezuela	−0.11

Source: J. C. B. Cooper, "World Stock Markets: Some Random Walk Tests," *Applied Economics*, October 1982.

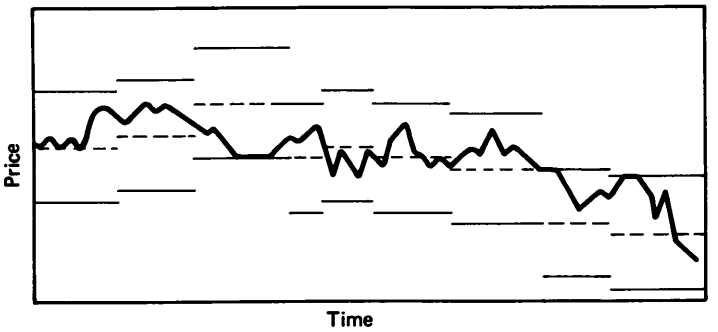

Figure 1.6
Hypothetical chart of a stock price that is free to wander within periodically changing limits.

Table 1.4
Average annual rates of return from filter rule, 1957–1962

Value of filter x	Return with trading strategy (%)	Total transactions with trading strategy	Return with trading strategy after commissions (%)
0.5	11.5	12,500	−103.6
1.0	5.5	8,700	− 74.9
2.0	0.2	4,800	− 45.2
4.0	0.1	2,000	− 19.5
6.0	1.3	1,100	− 9.4
8.0	1.7	700	− 5.0
10.0	3.0	400	− 1.4
20.0	4.3	100	3.0

Source: E. F. Fama and M. E. Blume, "Filter Rules and Stock Market Trading," *Journal of Business* 39 (January 1966):226–241.

If the daily closing price of a security rises at least x%, buy the security and hold it until its price moves down at least x% from a subsequent high. At that point sell the security short and maintain the short position until the price rises at least x% above a subsequent low.

By choosing a large value for the filter x, the investor would increase the probability that he is participating in a change in trend instead of merely a movement between barriers, but he would suffer the offsetting disadvantage of missing a large part of the move before he acted.

The first two columns of table 1.4 show the returns that you would have earned if you had used this filter rule to choose among the Dow Jones stocks during a five-year period.[6] Although the returns are positive, they are generally less than the 10 percent return you would have gotten if you had simply bought the Dow Jones stocks and left them alone. The remaining two columns of table 1.4 show both the number of transactions from following the filter strategy

and the returns after dealing costs. They suggest that in each instance the only solace for the adherent of the filter rule would have been the gratitude of his broker.

The relative strength rule is another popular technical rule.[7] Its adherents also seek to exploit price trends, but they choose to concentrate on each stock's relative performance. Here is an example of the relative strength rule:

Each month measure the strength of the stock price by calculating the ratio of the current price to the average price over the previous six months. Start by investing equal amounts in the twenty stocks with the highest relative strength. Then continue to hold each of these stocks as long as they remain in the top 160 stocks in terms of relative strength. If any stock drops below this position, sell it and reinvest the proceeds in the current top twenty.

To assess the merit of such a rule, five separate eligible lists of 200 stocks each were selected from the stocks listed on the New York Stock Exchange (NYSE) in 1960.[8] From each of these eligible lists a portfolio was selected and managed according to the relative strength rule. The average return on these portfolios at the end of five years was compared with the return from buying and holding each of the stocks listed on the NYSE.

The results of this comparison and of similar comparisons for earlier five-year periods are shown in table 1.5. When dealing costs are ignored, the return from the relative strength rule was on average 0.8 percent a year higher than the return from the buy-and-hold strategy, but when one takes account of the costs of following the relative strength rule, the advantage is reversed.

In bull markets it is the risky stocks that generally have the highest returns; in bear markets it is the safest stocks. Therefore by following the relative strength rule an investor will tend to invest in risky stocks after a market rise and in

Table 1.5
Difference between returns from relative strength rule and buy-and-hold strategy

Period	Number of portfolios	Return (%) Before costs	After costs	Risk-adjusted, after costs
1931–1935	**3**	**−1.9**	**−3.7**	**−2.7**
1936–1940	**3**	**−3.5**	**−4.7**	**−5.6**
1941–1945	**4**	**−0.3**	**−2.3**	**−1.4**
1946–1950	**4**	**−0.5**	**−1.7**	**−1.7**
1951–1955	**5**	**2.7**	**1.5**	**0.2**
1956–1960	**5**	**7.8**	**6.8**	**5.7**
1961–1965	**5**	**1.4**	**0.1**	**−0.2**
	Average	**0.8**	**−0.6**	**−0.8**

Source: M. C. Jensen, and G. A. Bennington, "Random Walks and Technical Theories: Some Additional Evidence," *Journal of Finance* 25 (May 1970):469–482

safe stocks after a market fall. More often than not the rule will produce portfolios with above-average risk. The final column of table 1.5 makes an adjustment for this difference in risk.[9] It shows that after dealing costs the risk-adjusted return from following the relative strength rule was on average 0.8 percent a year less than the risk-adjusted return from a simple buy-and-hold strategy.[10]

Stock Prices in a Well-Functioning Market

"October," Mark Twain observed, "is one of the peculiarly dangerous months to speculate in stocks in. The others are July, January, September, April, November, May, March, June, December, August and February." Although he was nearly right, there is some evidence that stocks perform better in January than in June. They also seem to perform better

on Wednesday than Monday.[11] These are two examples of patterns that appear to exist, but you will not get rich on the basis of such patterns. The evidence is remarkably unanimous; for most practical purposes stock prices seem to follow a random walk.[12]

Early reaction to this finding was that it confirmed everybody's suspicion that investors are a whimsical and unpredictable bunch. Only later did economists come to realize that the result was exactly what we should expect in well-functioning securities markets.

In a free and competitive market, the stock price at each point in time depends on each investor's assessment of the security's true value. It, therefore, incorporates all the information available to investors. If a fresh piece of information subsequently becomes available, its implications will be examined and will cause a new price to be established. Because information is only new when it has not been deduced from earlier information, its effect on prices will be quite independent of anything that may have happened earlier. In other words, each price change will be unrelated to previous price changes.

Suppose, however, that a small number of investors do gain prior access to information. If that information is going to justify a rise in price, the knowledgeable individuals will be able to secure a profit by buying ahead of the market. Their purchases will cause the price to shift part way toward its new equilibrium. Subsequently, when the new information becomes publicly available, the price rise caused by the purchases of the experts will be followed by a further rise. Thus successive price changes will be related when there is a spreading awareness of information, and they will be unrelated when information is immediately and fully reflected in the stock price.

The existence of a limited number of experts with superior information will lead to dependence between successive

prices. However, as long as the uninitiated are on their toes, such a situation cannot endure, for they will learn to spot what the experts are doing by examining past price changes and imitating the experts' behavior. If a sufficient number of buyers gain the advantage of the experts, the original situation is re-established. Each price change again becomes independent of the price changes that preceded it. Thus competition among fundamental analysts helps to ensure that information is rapidly discounted. And competition among technical analysts ensures that even if some investors do have superior information, their activities are rapidly discovered. In other words, both groups help keep stock price changes random.

Implications of the Random Walk Hypothesis

The term random has some unfortunate connotations. Random events are often believed to be in some sense "uncaused." This belief is partly due to misleading comparisons that are sometimes drawn between stock price changes and the behavior of a roulette wheel. The problem is liable to be translated into a philosophical one, but there is nothing mystical or unnatural about the process that generates stock price changes. It is not governed by some frolicsome gremlin. The random movement of stock prices simply results from competition between a large number of skilled and acquisitive investors.

A more specific misunderstanding is the view that the random walk hypothesis is inconsistent with a rising trend of stock prices. Regardless of whether the market is competitive, investors want a positive return for investing in risky securities. Moreover each of the tests that we have described has looked only at the sequence of price changes and has not been concerned with the average change.

It is sometimes suggested that the random character of stock price changes reflects unfavorably on the ability of the

investment community. This is not true. The ease of entry into the industry and the high potential rewards presumably ensure the supply of at least some very able people. Beyond this, any useful conclusions are impossible, for whereas the notion of a perfect market implies a certain amount of equality among some of the protagonists, it is also consistent with wholly aimless investment by others.

It is even more difficult to draw any conclusions about the social value of investment activity. The competitive nature of the market might severely limit the extent to which some investors are able to profit at the expense of others, yet the community in general and investors indirectly still benefit in the form of efficiently distributed capital resources. In the same way, it may be meaningful to judge the value of an individual football team by the proportion of matches that it wins, but the value of football teams in general must be judged by some other criterion, such as the amount of enjoyment they provide.

Technical Analysis and Random Walks

Because the random character of stock price changes suggests that investment is a very competitive pastime, it has indirect implications for the fundamental analyst, which we shall consider in the next two chapters. Here we are concerned with the finding's direct challenge to the technical analyst. His activities may contribute to the maintenance of independence between successive price changes, but the existence of this independence removes all scope for profit by examination of the sequence of past price changes.

Although the evidence suggests that technical analysis is an unproductive pastime, it is impossible to prove that there are no relationships between successive price changes. It, therefore, remains possible that patterns exist for some stocks for some periods. Good managers, however, bet on prob-

abilities, not possibilities. Given the evidence, it is difficult to justify setting out on a quest for the holy technical grail, and it is equally difficult to see how one could hope to be sure that any apparent regularity was not a passing coincidence.

If you are determined to embark on such a quest, it is important to be prepared for some of the snares that you may encounter. First, a number of apparently successful technical rules assume that information would have been available to the investor earlier than was in fact the case. One instance of this occurs when the sample from which the selection is to be made is both unrepresentative and unknown to the investor at the beginning of the period. For example, some years ago a senator gained considerable publicity with the claim that by throwing darts at the NYSE daily page of the Washington *Evening Star,* he had selected a portfolio that would have outperformed most mutual funds over the previous ten years. The senator had not considered that at the beginning of the period no investor would have had the benefit of knowing which stocks would have an NYSE quotation ten years later. Decision rules that assume the investor is aware of company earnings immediately after the end of the year suffer from a similar defect. In other cases, the trading rule is left vague. Certain apparent relationships between stock prices and other factors may be observed without any clear indication of how the relationship should be used or how to avoid signals that can be seen to be false only after the event.

Frequently the system is operable, but the profits are illusory and result from inadequate measures. For example, proponents of a particular technical rule often look only at capital gains and ignore differences in the dividend yield. On other occasions they may ignore the costs of switching from one stock to another. Or they may fail to recognize that the superior reward is needed to compensate for the

additional risk. Just as common stocks are expected to offer higher returns than bonds, so stocks with above-average risk are expected to offer higher returns than those with below-average risk.

With a little care it is possible to detect the systems that would never even have been successful in the past. However, the fact that a trading rule would have been profitable in the past is no guarantee that it will continue to be so in the future. If you examine a sufficient number of possible rules, you can be certain that eventually you will find one that would have been profitable over a particular past period, but this success may be no more than a coincidence. Repeated analysis of the same body of data is often known as data mining. It is unlike any other kind of mining, for the resource is never depleted, but all that you extract is fool's gold. If you must data mine, put aside some data from a different period to check whether the apparent patterns that you discover in the first sample really do persist.

It is a costly and tedious business to check the profitability of technical rules. But it is likely to be even more costly to use such a rule without first assessing its value. If the rule does not work, you will make unnecessary transactions and your portfolio will be poorly diversified. Faced with this unenviable choice, the wise investment manager ignores the siren song of the technical analyst.

Notes

1. This visual comparison was first suggested by Roberts (5).

2. See Fama (4).

3. See Fama (4).

4. See Cooper (1). Indexes of stocks that are infrequently traded may exhibit spurious patterns (see Working (7)). Despite this, the general impression in table 1.3 is that there is very little relationship between successive market movements.

5. The possibility of these barriers was suggested in Cootner (3).

6. See Fama and Blume (10).

7. The principal advocate of the relative strength rule is Levy (13, 14).

8. The tests described here are by Jensen and Bennington (12).

9. More precisely, it shows the difference between the return from following the relative strength rule and the return from holding an equally volatile package of risk-free loans and the market index. The rationale for such a measure is discussed in chapter 10.

10. Obviously there are countless variations on this relative strength rule. Jensen and Bennington also analyzed the results from buying ten rather than twenty stocks. The performance of these ten-stock portfolios was somewhat worse than that of the twenty-stock portfolios.

11. See references listed at the end of this chapter.

12. An excellent collection of the earlier studies on the random walk hypothesis is that of Cootner (2).

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(16) Cross, F. "The Behavior of Stock Prices on Fridays and Mondays." *Financial Analysts Journal* 29 (November–December 1973):2–69.

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(18)Gibbons, M. R., and Hess, P. J. "Day of the Week Effects and Asset Returns." *Journal of Business* 54 (1981):579–596.

(19) Rozeff, M. S., and Kinney, W. R., Jr. "Capital Market Seasonality: The Case of Stock Returns." *Journal of Financial Economics* 3 (1976):379–402.

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(20) Samuelson, P. A. "Proof that Properly Anticipated Prices Fluctuate Randomly." *Industrial Management Review* 6 (Spring 1965):41–49.