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Technical Anomalies: A Theoretical Review

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Abstract

The validation of weak-form efficient market hypothesis (EMH) depends on the testing of random walk hypothesis (RWH) and the non-presence of technical anomalies. Once technical anomalies are discovered based on the interpretation of technical analysis, investors can exploit these opportunities to earn above-normal returns from price forecasting. Thus, it violates the weak-form EMH. As the weak-form is violated, it would imply that all stronger forms of EMH are not supported. Hence, the issue of technical anomalies should not be ignored in the EMH study. This study focuses on the theoretical review of several important forms of technical anomaly, including short-term momentum, long-run return reversals, stock price volatility clustering, calendar anomalies, and technical rules. Based on the review of literature, we suggest that the persistence of anomalies over long-period horizon has remained controversial. In practical, the reliability of the forecast power of technical analysis is important to show the relevance of technical anomalies in the EMH domain.

Keywords: technical anomalies, short-term momentum, long-run return reversals, volatility clustering, calendar anomalies, technical rules

1 Introduction

For the onset, it is important to clarify what is meant by the terms ‘anomalies’ and ‘technical anomalies’. Anomalies are trading opportunities that arise from strategies by which stock trading can result in above-normal returns (Hubbard, 2008: 217). Technical anomalies are anomalies discovered based on the interpretation of technical analysis. In which, technical analysis leans against three elements, including security prices, the repeatability of price trends in the market, and the fact that prices tend to enroll in some trends. The common graphical analyses are such as: the trend line which is given by consecutive points or the minimum or maximum prices of securities or stock indices, to show the direction of an observed trend; configurations of reversibility which is used to indicate the minimum and maximum levels of prices, correlated with the possibility of trend reversal; the support lines which are the minimum levels of prices where the market does not fall below it, and thus signal that the interest of buyers is strong enough to face selling pressure; the resistance lines which are the maximum levels of prices where the market could reach, and thus indicate that the

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interest of sellers is strong enough to face the buying pressure; moving averages which are used to smooth the historical data for short-term or long-term in order to confirm the trend, using the methods of simple moving average, weighted moving average or exponential moving average; and gaps, the graphical configurations applied to confirm price movements (i.e. a gap is formed when the minimum price of a security in a given period is higher than the highest price of the previous period) (see Dana and Cristina, 2013). Such graphical analyses are useful tools in technical analysis, and are commonly applied in the stock price forecasting by technical analysts.

As far as past returns predictability is concerned, validating the weak-form EMH by only based on the testing of RWH using the commonly applied unit root tests method is considerable insufficient. In fact, the validity of weak-form EMH is much depending on the presence of technical anomalies. As Poterba and Summers (1987: 2) note, variance ratios are among the most powerful tests for detecting mean reversion in stock prices, but they have little power against the principal interesting alternatives to the RWH. In many previous studies, variance ratio and runs tests are seen useful to detect the presence of serial correlation in a stock series. Fama (1991) has suggested a broader coverage of weak-form EMH tests. This is a category of more general areas of test for returns predictability. In the category, it has covered the following areas of test: predicting returns from past returns (i.e. short-horizon returns, and long-horizon returns); predicting returns from other forecasting variables (i.e. expected inflation, short-term interest rates, dividend yield or dividend-price ratio, D/P, and earnings-price ratio, E/P); volatility tests; and seasonals in returns (Fama, 1991: 1576). However, Groenewold and Kang (1993: 408) show that, by estimating stock returns based on macroeconomic variables like money supply, real government expenditure, and price level, we can test for the semi-strong form EMH. Moreover, the D/P[1] and E/P[2] ratios reflect the fundamentals of stocks and thus are applicable to fundamental analysis. Therefore, they can be considered related to the semi-strong form EMH. In spite of using other forecasting variables, all the prior mentioned return predictability aspects are able to verify the presence of technical anomalies. Once a stock series is showing the presence of technical anomaly, market inefficiency is implied. If the weak-form EMH is violated, other stronger forms of EMH are not supported. In that sense, the issue of technical anomalies is significant in the domain of EMH.

1 Dividend-price ratio (D/P) is referred to as dividend per share divided by the price per share. It is a company's total annual dividend payments divided by its market capitalization. It is used to calculate the earnings on investment, that is, shares, considering only the returns in the form of total dividends declared by the company during the year. See http://en.wikipedia.org/wiki/Dividend_yield, retrieved on 7/4/2014.

2 Earnings-price ratio (E/P) is the inverse of price-earnings ratio (P/E). It is calculated by dividing the projected earnings per share by the current market price of the stock. Relatively low E/P anticipates higher-than-average growth in earnings, and vise-versa. See http://financial-dictionary.thefreedictionary.com/Earnings-Price+Ratio, retrieved on 7/4/2014.

This paper aims to provide a theoretical review of technical anomalies and offer a better understanding of the topic. The rest of the paper is organized as following: Section 2 is focused on short-term momentum; Section 3 is the review of long-run return reversals; Section 4 concentrates on stock price volatility clustering; Section 5 reviews about calendar anomalies; Section 6 is about technical rules; Last section concludes.

2 Short-term Momentum

Short-term momentum can be reflected by serial correlation or autocorrelation in stock prices (see French and Roll, 1986; Malkiel, 2003). That is, the prices are probable to keep moving in the same direction instead of changing to other directions. It is now a common practice to treat the terms 'autocorrelation' and 'serial correlation' synonymously (Gujarati, 2003: 443).[1] Which, autocorrelations involve a variable and a lag of itself, for example, the correlation between *YY* and *YY* lagged *PP* periods (see Koop, 2009: 139). Stock prices may exhibit autocorrelations over short periods, such as intra-day, in a week, over a few weeks, within a month, or over several months. Once short-term momentum is confirmed having reliable predictability power, the EMH is violated for the stock series studied.

Literature offers some plausible explanations to short-term momentum. The contribution of Malkiel (2003) is on describing how psychological feedback mechanisms and underreaction of investors to new information can cause positive serial correlations. Firstly, short-term momentum is seen as consistent with the psychological feedback mechanisms. The so called bandwagon effect is believed can arise from stock market trading. When investors see a stock price rising, they are drawn into the market. Thus, we may think of when the price of a stock is seen going to plummet, investors tend to get out from the market quickly. Such psychological feedback mechanisms explain the logic behind observable successive moves of stock price in the same direction. Secondly, short-term momentum can be a result of investors' underreaction to new information. It is possible that share prices do not fully adjust to new information immediately. If the full impact of an important news announcement is only grasped over a period of time, stock prices may exhibit positive serial correlation over the short-horizon.

Mispricing of stocks is a possible source of negative serial correlations. Stock can be mispriced and thus prices are not reflective of close intrinsic value for short periods, such as intra-day, weekly, monthly, and over weeks and months. French and Roll (1986) have documented two important factors in causing negative serial

3 Though, Gujarati (2003) clarified that these terms can be treated as different econometric terminologies, which autocorrelation is the lag correlation of a given series with itself, lagged by a number of time units, while, serial correlation is the lag correlation between two different series.

correlations in stock returns, namely, exchange holidays, and close-to-close returns. When concerning the factor of exchange holidays, both private information hypothesis and trading noise hypothesis would predict that, the return variances of stocks will be reduced and are unusually low on the trading day after exchange holidays, than on the trading day before exchange holidays. It is because prices adjust to corrections over some time. However, the public information hypothesis would predict that, there should be unseen significant reduction in return variances due to the factor of exchange holidays. Meantime, close-to-close returns normally contain measurement error because each closing trade may be executed at any price within the bid/ask spread. Thus, if these measurement errors are independent from day to day, we can expect that they will induce negative first-order autocorrelation of stock prices.

3 Long-run Return Reversals

Long-run return reversals are reflected from the evidences of negative serial correlation in stock returns over long period (see Malkiel, 2003: 63). Mean reversion of stock returns shows the tendency of stocks with high returns today to experience low returns in the future, and vice-versa (Hubbard, 2008: 218). Hence, it entails the returns predictability of the loser stock portfolios, as well as the winner stock portfolios. Stock price forecasts are possibly performed based on the past performance of particular stocks observed. Furthermore, the mean-reverting pattern of stock returns is presumed to be the anomaly of long-term returns which violates the EMH, until reliable exploitable trend for forecasting is clearly indicated.

In order to show the reasons of long-run return reversals, this review refers the underlying ideas of investors' overreaction to recent information (see De Bondt and Thaler, 1985), and the slowly decaying component contained in stock prices (see Summers, 1986; Fama and French, 1988). De Bondt and Thaler (1985) find that, the loser stock portfolios experienced exceptionally large January returns as late as five years after the portfolio formations. Investors tend to overreact to recent information such as earnings and underweight base rate data. As it is known that prices are initially biased by either excessive optimism or pessimism, therefore, once investors foresee that returns will exhibit mean-reversion over long period, they perceive prior loser stocks are more attractive investments than prior winner stocks. Investors can use a contrarian strategy, that is, by buying the neglected stocks, as they expect the prices of these stocks will rise in the long-run.

Meantime, mean reversion of stock returns over the long-horizon is concerned with the slowly decaying component contained in stock prices. The mean-reverting component in stock returns tends to induce negative autocorrelation over the short-horizon, such as, for daily and weekly holding periods, which is rather weak but stronger for stock returns of the long-horizon. In which, negative autocorrelation is likely to increase with time. This can explain why stock prices take long temporary swings away from fundamental values, and thus causing market inefficient (see Summers, 1986; Fama and French, 1988). However, Fama and French (1988) disagree with the anomaly discovered on this basis because random walk component is perceived still dominating in a stock series. Therefore, it is believed that such pattern may not have reliable predicting power which allows consistent earnings of above-normal returns. Timmermann and Granger (2004: 22) also argue on the reliability of anomalies. It is perceived that, once an anomaly has become publicly known, arbitrages will bring stocks back to intrinsic values. Thereby, anomalies tend to disappear from future samples. This complicates the use of statistical tests for price forecasting. Hence, the relevance of technical anomalies to the validation of the weak-form EMH has remained controversial.

4 Stock Price Volatility Clustering

In the literature of weak-form EMH, volatility tests belong to the area of the more general tests for EMH (see Fama, 1991: 1576). Volatility of stock prices is the tendency of stock prices to change or move in a trading range over time, whereby high volatility is characterized by a broad trading range and widely varying price trends, while low volatility is characterized by a narrow trading range and stable price trends (Thomsett, 2006: 187). Trading range can be referred to as the distance between a stock's established high and low prices over a period of time (Thomsett, 2006: 226). Stock market volatility can be either a normal volatility or jump volatility. A normal volatility appears as the ordinary variability of stock returns, like ups and downs in return. While, jump volatility is the occasional and sudden extreme changes in returns (Becketti and Sellon, Jr., 1989: 21). In addition, according to Becketti and Sellon, Jr. (1989), the concern of the excessive volatility of financial assets' prices is that, it may impair the smooth functioning of financial system and adversely affect economic performance.

In statistical terminologies, it is common practice to equate variance and volatility, and use variance as a measure of volatility. As discussed earlier, the random walk with drift model can be written as, $\Delta y_t = \alpha + e_t \Delta y_t = \alpha + e_t$ which $\Delta y^2_{t-1} \Delta y^2_t$ indicates the series with deviations from means taken, $\Delta y_t = \Delta y_t - \Delta y \Delta y_t = \Delta y_t - \Delta y_t$, where $\Delta y_t = \sum Y_t / T \; \Delta Y = \sum Y_t / T$. We can get the estimate of variance, $\Delta y^2_t \, \Delta y^{2t}_t$, by differencing the stock price data, taking deviations from means and then squaring it. The new time series data obtained is volatility. It is possible to use $\Delta y^2_t \Delta y^2_t$ as an estimate of volatility at time *tt*. High volatility is associated with big changes either in a positive or in a negative direction. As any number squared becomes positive, large rises or large falls in the price of an asset will imply $\Delta y^2_t \, \Delta y^2_t$ is positive and large. It is sensible to think of, in stable time, the asset price will not be changing much and therefore $\Delta y_t^2 \Delta y_t^2$ will be small. Thus, the measure of volatility will be small in stable times and large in chaotic times (see Koop, 2009: 183-184).

Once stock returns exhibit volatility clustering, as in Magnus (2008: 7), when large changes in stock returns are followed by large changes, and small changes by small changes, investors can exploit this knowledge to predict future stock prices. Koop (2009: 184) explains the use of autoregressive model to model clustering in volatility of financial time series data. For example, an AR (1) model that uses volatility as the time series variable of a financial series, as following:

$$\Delta y_t^2 = \alpha + Ø\Delta y_{t-1}^2 + e_t$$

The model describes that volatility in a period is depending on the volatility of previous period. If for instance, $Ø > 0Ø > 0$, then if volatility was unusually high last period, as $\Delta y_{t-1}^2 \, \Delta y_{t-1}^2$was very large, it will also tend to be unusually high this period. Otherwise, if volatility was unusually low last period, as $\Delta y_{t-1}^2 \, \Delta y_{t-1}^2$ was very low or near zero, this period volatility will also tend to be low. However, the presence of the error, $e_t e_t$, means that there can be exceptions to this pattern. Though, this model hints that there tend to be intervals or clusters in times where volatility is low, and alternatively intervals or clusters where it is high. If such patterns allow for reliable price forecasting, then anomaly is considered present and the EMH is violated.

5 Calendar Anomalies

The dimension of seasonals in returns is well-accepted in the area of weak-form EMH studies. Calendar anomalies are abnormal stock returns associated with the turn of the year, the month, and the week, and they tend to occur at turning points in time (Karadžić, 2011: 110). For example, some seasonals in returns are consistent recurring patterns of stock series on the basis of weekly, monthly, or yearly. As such, calendar anomalies can arise from seasonals in returns. There are considerable calendar anomalies given by literature, including: turn-of-the-year effect, also known as the January effect, which is an increase in buying securities before the end of the year at a lower price, in order to sell them in January to generate profit from the price differences; the holiday effect, that is, the tendency of the market to do well on any day which precedes a holiday; turn-of-the-month effect, which is the tendency of stock prices to increase during the last two days and the first three days of each month (see Karadžić, 2011); and day-of-the-week effect, as investors can buy stocks on days with abnormally low returns and sell stocks on days with abnormally high returns (Basher and Sadorsky, 2006: 621).

6 Technical Rules

Some technical rules are documented in literature as having predicting power. Therefore, it is possible that anomalies can arise from technical rules. According to Karz (2010), two well-accepted technical rules are moving average and trading range break. In which, moving average shows that all the buy and sell signals are generated by a long and short moving average crossing. For example, by testing long moving averages of 50, 150 and 200 days with short averages of 1, 2 and 5 days, in order to observe whether the buy-sell differences are positive and also whether the t-tests for these differences are highly significant. Meanwhile, trading range break is used to refer support and resistance levels of security prices or indices. Technical analysts are seen believing that investors sell at the resistance level and buy at the support level. Hence, when the price penetrates the resistance level, it signals buying, and when the price penetrates the support level, it signals selling.

7 Conclusion

In sum, literature shows several important forms of technical anomaly, including short-term momentum, long-run return reversals, stock price volatility clustering, calendar anomalies, and technical rules. The long-term nature of technical anomalies is subject to controversial. Some economists argue that anomalies do not persist over long-period horizon, thereby are not reliably exploitable for above-normal returns in the long-run (i.e. Fama and French, 1988; Timmermann and Granger, 2004). The argument reflects strong believe in the validity of EMH which implies that stock series are characterized by a random walk process. Nonetheless, it is unavoidable to take into account the presence of technical anomalies when validate the weak-form EMH. When a stock series shows predictable pattern which can be reliably exploited for earning above-normal returns, the weak-form EMH can be rejected. In that sense, it is important to assess the practical reliability of the forecast power of technical analysis. An anomaly may disappear once it is known to public. Arbitrageurs may bring stocks back to their intrinsic values. In that case, the value of technical analysis is neglected.

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