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SEVEN PITFALLS OF TECHNICAL ANALYSIS

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Abstract

This paper examines the main drawbacks of technical analysis. Although this is widely used by practitioners, from an academic perspective it can only be seen as a form of "voodoo finance". In particular, it runs into the following pitfalls: Subjectivity; Doubtful assumptions; Unjustified algorithms; Low profitability; Data snooping; Statistically insignificant results; Unrealistic simplifications. The key conclusion is that it is high time that (self-fulfilling) technical analysis be replaced by more sophisticated time-series forecasting methods and models such as fractional integration, R/S analysis and autoregressive specifications.

Keywords: *Technical Analysis; Data Snooping; Financial Markets; Price Forecasting; Trading.*

JEL Classification: *C63, D84, E37, G12*

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Introduction

Forecasting asset prices is crucial for traders and investors. However, it is not a straightforward task given the huge number of factors possibly affecting financial markets. The idea that price behaviour is best understood in terms of the random walk model was first introduced by Bachelier (1900). The underlying theory based on the concept of price unpredictability was subsequently developed by Fama (1970) with his Efficient Market Hypothesis (EMH) and its implication that investors cannot "beat" the market. Despite its simplicity and beauty, this framework has been highly criticized since the 1980s because of the apparent lack of empirical support for it. In particular, substantial evidence has been gathered of price anomalies such as calendar anomalies (e.g., the day of the week effect, the month of the year effect, etc. – Plastun et al., 2022), expiration day effects (Stoll and Whaley, 1987), price overreactions (Caporale and Plastun, 2022), price bubbles (Porter and Vernon, 2003), fat tails in price distributions (Peiro, 1994), persistence (Caporale et al., 2018) etc., all suggesting the existence of predictable price patterns potentially exploitable by investors to make abnormal profits, in contrast with the EMH.

Various explanations have been put forward to account for this discrepancy between theory and empirical evidence, the most popular ones drawing on behavioural finance studies (Shiller and Akerlof, 2009; Thaler, 1993). The basic idea in this literature is that market participants are irrational, this being the reason why prices deviate from their fundamental values. Some of the cognitive traps are well known (representativeness bias, overconfidence, overreactions, crowd effects etc.), so in theory it should be possible to predict prices taking them into account. However, it is debatable whether or not most investors can be characterised in this way; moreover, one should not ignore the possibility that they can learn and adapt (as postulated by the adaptive market hypothesis). For these reasons, there is no consensus among academics not only on the type of model one should use to forecast prices (whether, for instance, VAR or ARIMA specifications should be preferred), but also on the more fundamental issue of whether prices are predictable at all. By contrast, practitioners (traders, brokers, dealers, investors, analysts etc.) almost invariably resort to technical analysis for this purpose, as shown by various surveys (Taylor and Allen, 1992; Cheung and Chinn 2001).

The basic idea of technical analysis is that prices contain all the relevant information and thus there is no need to examine how they are determined by fundamentals, price charts already being fully informative. In fact the Group of Thirty survey indicated that 97% of bank respondents and 87% of the securities houses believed that the use of technical analysis had a significant impact on the market (Griffioen, 2004). Also, Taylor and Allen (1992) found that at least 90 percent of foreign exchange dealers give some weight to technical analysis when forming their views, and Menkhoff (1997) reported that 87% of them use it for their decision making. Further evidence of the popularity of technical analysis is represented by the number of published textbooks on this topic, which include those by Murphy (1999 – a bestseller in Financial Risk Management on Amazon), Wilder (1978), Pring (1998), Schwager (1999), Edwards and Magee (2010) and DeMark (1994) – these being only the best known among many others. However, this approach has many limitations. Below, we highlight seven pitfalls that one runs into when following it.

Pitfall #1: "Subjectivity"

Pring (1991) makes the following statement concerning technical analysis: "…The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed". The key point to note is that, whilst science is characterised by "objectivity", technical analysis as an art belongs to the sphere of "subjectivity". As a result, different technical analysts can generate different forecasts for the same asset at the same point in time, and their approach is often described as "voodoo finance".

Pitfall #2: "Doubtful assumptions"

The three main assumptions of technical analysis are the following (see CFA, https://www.cfainstitute.org/en/membership/professional-development/refresher-readings/technical-analysis):

1. Markets discount everything, and therefore looking at prices will suffice.

2. Prices are trended (upwards or downwards).

3. History repeats itself.

Each of them is at least questionable. Specifically, forecasting models incorporating fundamentals have been found to outperform simple univariate ones (MacDonald and Taylor, 1994). Further, price charts normally show that there are periods when prices fluctuate randomly as well as others when they follow upward or downward trends. This is confirmed by the evidence on persistence in financial markets. For instance, Caporale et al. (2018) find that it changes over time in the case of the cryptocurrency market, which exhibits long-memory properties – this implies that price behaviour is not stable. Finally, there is no statistically significant empirical evidence that history repeats itself. For example, Levy (1971) tests the predictive power of 32 different chart patterns and finds no evidence that the corresponding forecasts can be the basis for profitable trading.

Pitfall #3: "Unjustified algorithms"

Technical analysis often relies on numbers or proportions (for example, Fibonacci, Elliot Waves, Rays of Gunn). However, there is no reason why these should be equally applicable for the purpose of price prediction. In particular, technical analysis often uses indicators to predict price behaviour, with trend indicators being based on price trends and oscillators on price reversals. Two of the most popular oscillators are known as "Momentum" and "Relative Strength Index" ("RSI") respectively, and defined as follows:

$$Momentum = \frac{PriceClose(current\ period)}{PriceClose(n\ periods\ ago)} \times 100 \tag{1}$$

and

$$RSI = 100 - \frac{100}{1 + RS}$$

where

$$RS = \frac{Average\ Gain}{Average\ Loss}$$

the average gain or loss being defined as the average percentage one during a look-back period.

In fact, neither of the above provides any useful information about future prices. Both of them are simply random algorithms which can only generate random results.

Pitfall #4: "Low Profitability"

Technical analysis is in fact not a profitable approach, as argued by Osler and Chang (1995). To illustrate this point, let us consider a trading strategy based on an RSI oscillator. The results are reported in Table 1.

Table 1. Profitability of a trading strategy based on the RSI indicator

Parameter/Period	2017	2018	2019	2020	2021
Number of trades	104	107	97	97	97
Number of successful trades	63%	60%	57%	58%	62%
Financial result	-30	-171	-180	-672	-17
Absolute drawdown	134	698	446	1006	442

As can be seen, the total number of trades is more or less stable, whilst the successful ones fluctuate around 60% of the total, which suggests potential profits from trading. However, the other parameters vary considerably over time, which implies that there is no guarantee that the trading strategy will be profitable. In fact, it turns out to be unprofitable (i.e., the financial result is negative) in all periods. The absolute drawdown (the difference between the initial deposit and the minimum point below the deposit level) is also unstable and much greater than the financial result. Thus, there is a negative risk/profit ratio for the trading strategy based on the RSI indicator.

Pitfall #5: "Data snooping"

Textbooks provide many examples of technical analysis producing accurate forecasts resulting in profitable trades. However, this is simply a case of "Data Snooping": it is no wonder that out of the huge number of indicators and methods used by technical analysts (such as trading algorithms based on different parameters) some should result in profitable trading strategies - this is not due to their better forecasting performance, it is just a random occurrence (Griffioen, 2004). To put it another way, if one has sufficient computing time, one can always find a mechanical trading rule generating profits (Jensen and Benington, 1969).

To illustrate data snooping in technical analysis, we have developed a trading strategy based on a random trading rule, specifically a "Morning Buy" one defined as follows: buy EUR/USD at the beginning of the American trading session and close the opened trade position before the end of the session. There is clearly no rationale for such a strategy, which is based on the assumption of a positive trend for the EUR/ USD exchange rate, despite the fact that no evidence has been obtained of the existence of such a trend. Thus, there is no reason for such a strategy to be profitable. Nevertheless, following this strategy in the first four months of 2011 would lead to the conclusion that it is highly profitable. The results for a trading account of USD 1000 were as follows (see Table 2):

Table 2: Results for a "Morning buy" strategy during the first four months of 2011

Month	Profit/loss	Profitability	Annual profitability
January	142	14%	170%
February	127	13%	152%
March	276	28%	331%
April	209	21%	251%

However, using the same strategy in the following month (in May 2011) would produce a monthly return of -59%, which would wipe out all the previous gains. In fact over the whole of 2011 (or 2010) the entire initial deposit would be lost if one followed this strategy. But by selecting a specific sample one can always reach the (misleading) conclusion that a particular strategy is profitable.

Pitfall #6: “Statistically insignificant results”

The fact that a trading strategy generates profits could simply be a random outcome which has nothing to do with the strategy itself, since random trading can generate profits from time to time. Relevant examples can be found in Caporale and Plastun (2022) or Plastun et al. (2022). The use of simple z-tests shows that in many cases profits from a given trading strategy are not statistically different from those from random trading. Statistical significance tests are necessary to draw any conclusions about profitability (Sullivan et al., 1999). More sophisticated methods such as White's Reality Check could also be used (White, 2000).

Pitfall #7: “Unrealistic simplifications”

Technical analysis is often based on unrealistic simplifications. For example, transaction costs (spreads, transfer and banking fees, broker commissions etc.) are frequently overlooked when assessing the profitability of trading strategies. Kuang (2010) showed that among nearly 26,000 option trading strategies based on technical analysis there are thousands of seemingly profitable ones, but almost all of them turn out to be unprofitable when transaction costs are incorporated.

Conclusions

Technical analysis is very widely used by financial markets participants. However, from an academic perspective it can be considered as no more than “voodoo finance”. In particular, we have highlighted its main seven pitfalls: Subjectivity; Doubtful assumptions; Unjustified algorithms; Low profitability; Data snooping; Statistically insignificant results; Unrealistic simplifications.

The major argument in favour of technical analysis is that many traders use it, and therefore it may influence market prices as a self-fulfilling prophecy. But this is certainly not a sufficient reason to rely on it rather than using more sophisticated scientific methods. For instance, nowadays a wide range of techniques are available to measure persistence, such as fractional integration, R/S analysis, detrended fluctuation analysis, multifractal generalization etc. As for forecasting, different types of time series models (AR – autoregressive models, ARMA - autoregressive–moving-average, ARIMA - autoregressive integrated moving average, VAR - vector autoregression, etc.) can be estimated to predict future prices using appropriate model selection criteria (information criteria such as AIC - Akaike information criterion, BIC - Bayesian information criterion, MML - Minimum message length method, etc.). It is high time that technical analysts start using such methods to gain a deeper understanding of price behaviour as the basis for their trading strategies.

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