The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis

Lukas Menkhoff
Leibniz Universität Hannover

and

Mark P. Taylor
University of Warwick
and
Centre for Economic Policy Research

Discussion Paper 352
November 2006
ISSN: 0949-9962

Abstract

Technical analysis involves the prediction of future exchange rate (or other asset-price) movements from an inductive analysis of past movements. A reading of the large literature on this topic allows us to establish a set of stylised facts, including the facts that technical analysis is an important and widely used method of analysis in the foreign exchange market and that applying certain technical trading rules over a sustained period may lead to significant positive excess returns. We then analyze four arguments that have been put forward to explain the continuing widespread use of technical analysis and its apparent profitability: that the foreign exchange market may be characterised by not-fully-rational behaviour; that technical analysis may exploit the influence of central bank interventions; that technical analysis may be an efficient form of information processing; and finally that it may provide information on non-fundamental influences on foreign exchange movements. Although all of these positions may be relevant to some degree, neither non-rationality nor official interventions seem to be widespread and persistent enough to explain the obstinate passion of foreign exchange professionals for technical analysis.

JEL-Classification: F 31
Keywords: foreign exchange market, technical analysis, market microstructure

*The authors are grateful to Carol Osler, Stephan Schulmeister, Roger Gordon and anonymous referees for helpful comments on an earlier version of this paper. Menkhoff gratefully acknowledges financial support from the German Research Foundation (Deutsche Forschungsgemeinschaft DFG).

November 2006

Lukas Menkhoff
Department of Economics
Leibniz Universität Hannover
Königsworther Platz 1
D-30167 Hannover, Germany
menkhoff@gif.uni-hannover.de

Mark P. Taylor
Department of Economics
University of Warwick
Coventry CV4 7AL, UK
Mark.Taylor@warwick.ac.uk

"As for the foreign exchange, it is almost as romantic as young love, and quite as resistant to formulae."

— H. L. Mencken

1 Introduction

Technical analysis involves the prediction of future exchange rate (or other asset-price) movements from an inductive analysis of past movements, using either qualitative methods (e.g. the recognition of certain patterns in the data for visual inspection of a time-series plot) or quantitative techniques (e.g. based on an analysis of moving averages), or a combination of both. For professional economists, the widespread, continuing use of these techniques in the foreign exchange market (Taylor and Allen, 1992; Cheung and Chinn, 2001) is somewhat puzzling, since technical analysis eschews scrutiny of economic fundamentals and relies only on information on past exchange rate movements that, according to the weakest notion of market efficiency, should already be embedded in the current exchange rate, making its use either unprofitable or implying that any positive returns that are generated are accompanied by an unacceptable risk exposure.[1] On the other hand, despite an apparent emerging consensus that fundamentals such as relative prices or relative monetary velocity are capable of explaining very long-term exchange rate movements (Taylor and Taylor, 2004), there is still no fundamentals-based exchange rate model available that is capable of forecasting exchange rate behaviour over the shorter term (e.g. over a horizon of twelve months or less: Frankel and Rose, 1995; Taylor, 1995). Hence, the suggestion of Malkiel (1996), that "Technical strategies are usually amusing, often comforting, but of no real value" is perhaps a little too dismissive, and this has been recognised by a number of researchers.[2] Indeed, over the past twenty years or so, international financial economists have increasingly turned their attention to the study of technical analysis in an attempt to understand both the behaviour of foreign exchange rates and the behaviour of foreign exchange market participants; so much so, in fact, that quite an extensive literature has developed on this topic.

Although the literature on the application of technical analysis to the foreign exchange market is sufficiently developed to warrant a survey of its own, however, the foreign exchange market cannot be viewed in total isolation from other financial markets, and so we occasionally stray into the literature on the application of technical analysis to financial markets more generally and to equity markets in particular. The foreign exchange market differs from equity markets in some important aspects, however. First, total turnover in the global foreign exchange market is very high, at some 2,000 billion US dollars per day (Bank

[1] In other words, the ratio of expected return to risk (the volatility of returns) is unacceptably low.

[2] As we discuss in more detail below, Malkiel's dismissive treatment of technical analysis is at odds with the evidence that technical analysis is widely used by financial market traders.

for International Settlements, 2005), which is several times greater than the combined daily turnover of the largest stock exchanges in the world.[3] Second, foreign exchange markets consist almost entirely of professional traders (Sager and Taylor, 2006), so that the impact of individual private investors may be neglected without loss of generality (in contrast to equity markets—see, e.g., Griffin, Harris and Topaloglu, 2003). Third, the share of short-term interdealer trading is much higher in the foreign exchange market than it is in stock markets (Lyons, 2001). Finally, one can probably say that there is less confidence among traders in models of fair value in the foreign exchange market compared to equity markets (Frankel and Rose, 1995; Taylor, 1995; Campbell, Lo and MacKinlay, 1996). The greater lack of consensus in models of fair value in the foreign exchange market and the greater concentration on shorter trading horizons might suggest that the use of technical analysis would be more popular in the foreign exchange market, although the high proportion of professional traders and deeper liquidity of the foreign exchange market might suggest the opposite. However, we do not want to dwell too long on the differences between the foreign exchange market and equity markets, but rather emphasise the fact that foreign exchange is increasingly seen as a separate asset class (Snyder, 2005).

In this paper, we provide a selective and critical overview of the literature on technical analysis in the foreign exchange market. At the forefront of our discussion throughout is the question as to why technical currency analysis is so intensively and widely used by foreign exchange professionals. As an organising device, we develop a set of stylized facts concerning the importance and profitability of technical currency analysis. We then offer four different kinds of explanation for the persistent use of technical analysis and analyze the supporting evidence in each case.

2 The nature of technical analysis

Technical analysis or, as it also sometimes called, "chartist analysis" is a set of techniques for deriving forecasts of financial prices exclusively by analyzing the history of the particular price series plus perhaps transactions volumes.[4, 5] This analysis can be performed in a

---

[3] Comparing spot market turnover yields a ratio of about three in favour of the foreign exchange market compared to equities. We calculate this by taking daily spot trading in equities and currencies in 2004-5 in the seven largest asset trading centres in the world. For equities these were the New York Stock Exchange, Nasdaq, the London Stock Exchange, the Tokyo Stock Exchange, Euronext (Paris, Brussels, Amsterdam, Lisbon), the Deutsche Börse (Frankfurt) and the Bolsas y Mercados Españoles (Spain) (see the website www.world-exchanges.org), while for foreign exchange the major centres were London, New York, Tokyo, Singapore, Frankfurt, Hong Kong and Sydney (Bank for International Settlements, 2005). In these centres, daily spot market turnover was about 480 billion US dollars in foreign exchange versus 160 billion US dollars in equities; both figures represent more than 75 percent of the respective world markets.

[4] In this paper, we use the terms "technical analysis" and "chartist analysis "and their derivatives largely as synonyms. This usage is not universal, although it is not unusual among practitioners (see e.g. Henderson, 2002) and has some precedence in the academic literature (e.g. Goodhart, 1988; Frankel and Froot, 1990; Taylor and

qualitative form, relying mainly on the analysis of charts of past price behaviour and loose inductive reasoning, or it can be strictly quantitative, by constructing trading signals or forecasts through a quantitative analysis of time series data. In practice, technical analysts employ a combination of both qualitative and quantitative techniques.

Clearly, technical analysis assumes that price developments display regular, recurring patterns, otherwise such a purely inductive technique would be useless. A second condition for the profitability of technical analysis is that these patterns must last long enough, first to be recognized, and second to make up for transaction costs and false signals.

The more qualitative aspect of technical analysis involves recognising patterns in the data that are thought to herald trend reversals, such as “flags”, “head and shoulders” patterns, and so on (see e.g. Allen and Taylor, 1992).

The more widely used quantitative forms of technical analysis generally involve methods such as moving averages in order to exploit trends in the data. They thus attempt to distinguish trends from noise, i.e. fluctuations around a trend, by smoothing currency returns.

A simple moving average rule would signal an imminent break in trend, or the emergence of a new trend, when the moving average is crossed by the spot rate or by a shorter moving average. Thus, an imminent upward break in trend for the spot rate, s_t, might be signalled by a short moving average of length $m>1$, $MA_t(m)$, intersecting from below a longer moving average of length n ($n>m$), $MA_t(n)$, i.e.

$$MA_{t-1}(m) < MA_{t-1}(n) \;\; and \;\; MA_t(m) > MA_t(n), \;\; m < n,$$

where

$$MA_t(j)\frac{1}{j}\sum_{i=0}^{j-1} s_{t-i}\,,\; j = m, n \;\; .$$

Conversely, a downward break in trend would be signalled by the short moving average crossing the long moving average from above.[6] Indicators of this kind will tend to be profitable in markets exhibiting definite trends and so they are generically known as “trend-following” or “momentum” indicators.

Another widely used device is the “overbought/oversold” indicator, or oscillator. Oscillators are measures designed to indicate that price movements in a particular direction have recently been too rapid and that a correction in the opposite direction is imminent; they

Allen, 1992). It should be noted, however, that some practitioners and some authors differentiate “chartist analysis” as denoting the use of largely visual analysis of charts and therefore see it as a subset of the methods denoted by “technical analysis” (see, e.g., Neely, 1997).

[5] See Allen and Taylor (1992) for an outline of the origins of technical analysis.

[6] A variant would be to use exponential moving averages rather than simple arithmetic moving averages. Also, analysts may smooth the data prior to any analysis by applying very short-run (e.g. one-day) moving averages or exponential moving averages to the data, in order to reduce the effect of noise on trading signals.

may take a number of precise forms. One popular form is the relative strength indicator (RSI; Wilder, 1978), for example, which is defined as:

$$RSI_t = 100\frac{U_t}{U_t + D_t}$$

where U_t denotes the cumulated "up movement" (i.e. the close-to-close increase on a day when the exchange rate has closed higher than the previous day's closing rate) over a certain period, and D_t denotes the cumulated absolute "down movement" (the absolute close-to-close decrease on a day when the exchange rate has closed lower than the previous day's closing rate) over the same period (often fourteen days):[7]

$$U_t = \sum_{i=1}^{m} \iota(s_{t-i} - s_{t-1-i} > 0)(s_{t-i} - s_{t-1-i})$$
$$D_t = \sum_{i=1}^{m} \iota(s_{t-i} - s_{t-1-i} < 0)\,|\, s_{t-i} - s_{t-1-i}\,|$$

(where $\iota(.)$ is an indicator variable that takes the value one when the statement in parentheses is true, and zero otherwise).[8] The RSI thus attempts to measure the strength of "up movements" relative to the strength of "down movements", and is normalised to lie between 0 and 100; common values at which a particular currency is deemed to have been overbought (signalling an imminent downward correction) or oversold (signalling an imminent upward correction) are 70 and 30, respectively (see, e.g. Henderson, 2002). Indicators of this kind are also referred to as "reversal" indicators, since they are designed to anticipate a reversal in trend.

A third standard quantitative technique of technical analysis, the filter rule, involves buying a currency against another currency whenever the exchange rate has risen by more than a given percentage above its most recent low and selling it when the rate drops by more than the same percentage below its most recent high. An x-percent filter rule may be expressed thus:[9]

---

[7] Some expositions define U_t and D_t in terms of average rather than cumulated up and down movements. This is equivalent to our definition, however, since it just involves dividing by the total number of days and this factor cancels out when the RSI is calculated.

[8] The *RSI* is sometimes equivalently defined as $RSI_t \equiv 100 - 100\left(\frac{1}{1+RS_t}\right)$, where *RS*, or "relative strength", is defined as $RS_t \equiv U_t / D_t$.

[9] Note that the 'min' conditions in these filter-rule formulae minimise with respect to the *time period* rather than the *exchange rate*, so that they find the most recent period when the conditions indicated are met. For example, the formula for the buy signal may be expressed thus: "Starting at time *t*, find the most recent period in which the

Buy: $$100\frac{\left\langle s_t - \{s_{t-i} \mid i = \min[i > 0 \mid (s_{t-i} - s_t) < 0 \ \& \ (s_{t-i} - s_{t-1-i}) < 0]\}\right\rangle}{\{s_{t-i} \mid i = \min[i > 0 \mid (s_{t-i} - s_t) < 0 \ \& \ (s_{t-i} - s_{t-1-i}) < 0]\}} > x\%$$

Sell: $$100\frac{\left\langle \{s_{t-i} \mid i = \min[i > 0 \mid (s_{t-i} - s_t) > 0 \ \& \ (s_{t-i} - s_{t-1-i}) > 0\ ]\} - s_t\right\rangle}{\{s_{t-i} \mid i = \min[i > 0 \mid (s_{t-i} - s_t) > 0 \ \& \ (s_{t-i} - s_{t-1-i}) > 0\ ]\}} > x\%$$

Obviously, the variety of both qualitative and quantitative techniques varies enormously—a fact which makes it quite difficult to provide a systematic assessment of technical analysis. Moreover, empirical tests of specific rules and their associated trading signals are not fully satisfactory as tests of the efficacy of technical analysis more generally, since users typically do not apply a single rule but rather a range of technical indicators which they update on a non-regular basis. In addition, many technical analysts will also apply considerable market intuition to complement their quantitative conclusions, so there remains always a major element of subjectivity with the application of technical analysis.

3 The importance of technical analysis in the foreign exchange market

The widespread use of technical analysis by foreign exchange professionals was first brought to the attention of academic researchers by Goodman (1979), Group of Thirty (1985), Frankel and Froot (1986, 1990a, 1990b) and Goodhart (1988).[10] However, the existence of technical analysis and even its use did not provoke sustained academic interest as long as the available evidence was not of a more systematic nature. The scepticism with which academic economists initially viewed (and to some extent continue to view) technical analysis was derived largely from the intellectual standing of the efficient markets hypothesis (EMH), which, even in its 'weak form' (Fama, 1970), maintains that all relevant information should already be embodied in asset prices, making it impossible to earn excess returns on forecasts based on historical price movements, once suitable risk-adjustment is made.[11]

Nevertheless, during the 1990s, beginning with the work of Allen and Taylor (1990), a number of academic studies appeared that reported the results of surveys of foreign exchange market participants concerning the use of technical analysis. The salient characteristics of

---

exchange rate was less than it is at time *t* but where it had been falling compared to the previous period (i.e. the exchange rate's most recent low) and if the exchange rate has risen by more than x percent since then and time *t*, buy." The non-negativity condition on the *i* subscripts is to ensure that the formulae apply to lags rather than leads. (Naturally, it is understood that "buy" means "buy the currency whose price in terms of the second currency is represented by the exchange rate in question", and "sell" is to be interpreted similarly.)

[10] The early study of technical analysis in the foreign exchange market of Poole (1967) can be seen as very much ahead of its time.

these studies—in terms of survey year, target group, response rate, location, etc.—are given in Table 1. The first survey, discussed in Allen and Taylor (1990) and Taylor and Allen (1992), was carried out among chief foreign exchange dealers at financial institutions located in London in 1988; the most recent was conducted in 2001 by Gehrig and Menkhoff (2004) among foreign exchange dealers and fund managers located in Germany. In all, the various surveys have covered foreign exchange professionals based in London, Frankfurt, Hong Kong, Singapore, Tokyo, New York and Zurich. In 1995—the mid-point between the earliest and latest studies—the Bank for International Settlements (2005) ranked the seven locations covered by the survey studies as first to seventh in terms of daily turnover in foreign exchange dealing, making up about 78% of the total global turnover; the combined market share of these centres was virtually unchanged until 2004. Although the response rates of the studies differ markedly, the results are remarkably invariant.

The studies of Allen and Taylor (1990) and Taylor and Allen (1992) documented for the first time systematically that technical analysis is, indeed, an important tool in decision making in the foreign exchange market. They further established a perceived complementarity among market practitioners in the use of technical and fundamental analysis, and showed that reliance on technical analysis was skewed towards shorter trading or forecast horizons. These three basic findings are also features of the results reported in the remaining six survey studies (see Table 2), and therefore form the first three of our stylised facts—*SF1*, *SF2* and *SF3*:

Stylised Fact 1 (SF1): *Almost all foreign exchange professionals use technical analysis as a tool in decision making at least to some degree.*
Stylised Fact 2 (SF2): *Most foreign exchange professionals use some combination of technical analysis and fundamental analysis.*
Stylised Fact 3 (SF3): *The relative weight given to technical analysis as opposed to fundamental analysis rises as the trading or forecast horizon declines.*

SF1 can be established from the third column in Table 2. Those surveys which asked respondents whether or not they used technical analysis at some horizon found that around 90% or more did so. The fact that practitioners use technical analysis does not by itself, however, establish that they regard it as of major importance—they may attach *some* weight to it, but only a low weight. Although not identical in design, most of the surveys therefore also asked respondents to quantify the weight given to technical analysis relative to fundamental analysis at various horizons (*SF2*); the average relative weight assigned to

[11] The more extreme form of the EMH assumes that agents are risk neutral so that significantly non-zero excess returns cannot be earned.

technical analysis is shown in column five of Table 2, and ranges from around 30 percent to a little over 50 percent.

A further aspect of the importance of technical analysis concerns its use among various groups of market participants, since a high average score could mask its concentration in small subgroups in the market. Table 3 reveals, however, that technical analysis is perceived as important relative to fundamentals across a range of practitioner groups such as chief foreign exchange dealers, international portfolio managers and others, whatever their specific role in foreign exchange trading may be.[12]

Early analytical studies of the foreign exchange market that allocated a role to technical analysts or chartists tended to view chartists and fundamentalists as competing factions, either in their own right as traders or as advisers to traders (Goodhart, 1988; Frankel and Froot, 1990, 1990a). *SF2*, however, (*"Most foreign exchange professionals use some combination of technical analysis and fundamental analysis"*) challenges this adversarial view of chartism and fundamentalism. Figure 1 demonstrates that other studies have basically reproduced this finding of perceived complementarity (i.e. a reliance on fundamental *and* technical analysis) established by Taylor and Allen (1992). In particular, the weight given to strong mutual exclusiveness of chartism and fundamentalism, i.e. a reliance on *either* fundamental *or* technical analysis (represented in Figure 1 by values 9 and 10), is at most ten percent of respondents in all studies.

Finally, *SF3* states that technical analysis tends to be perceived as less important at longer horizons in comparison with fundamental analysis (see explicitly Taylor and Allen, 1992, Table 3B). A graphical presentation of the research regarding *SF3* can be seen from the work of Taylor and Allen (1992), Lui and Mole (1998) and Oberlechner (2001) in Figure 2A. These three studies relate the perceived relative importance of technical and fundamental analysis with forecast or trading horizon. If one takes, however, the other studies—featured in Figure 2B—into account, the result remains unchanged for the medium and longer horizons but becomes less clear for the very short horizon. There is, however, an obvious reason for this apparent difference in perceived relative importance at the very short horizon, in terms of their coverage of analytical tools or price-determining factors. In particular, studies featured in Figure 2B also take into account other factors such as the perceived importance attached by market practitioners to information on order flow (i.e. on information relating to the value of foreign exchange transactions signed according to the originator of the trade—see e.g. Ito,

[12] Overall foreign exchange trading operations will be headed by a chief dealer who is, however, due to his management role, not necessarily the most active trader. Then there will be core traders, such as those responsible for spot trades in a given exchange rate, and finally there are other foreign exchange traders who may focus on further objectives such as trading forwards and futures, or are junior and thus have less leeway in

Lyons and Melvin, 1998; Lyons, 2001; Sarno and Taylor, 2001; Evans and Lyons, 2002). The inclusion of factors other than technical and fundamental analysis in the menu of choices offered to survey participants thus dilutes the relative score given to technical analysis in the shorter-term domain (see on these factors columns two and four in Table 2).[13] Considering only fundamental and technical analysis for the purpose of comparison, indeed reproduces the earlier finding in Figure 2C (also supported by Gehrig and Menkhoff, 2006, with a different methodology).

As a final remark it may be reassuring that the stylised facts shown for foreign exchange dealers and fund managers from the main financial centres by and large also hold for financial journalists (Oberlechner, 2001) and dealers in an emerging market (Bhanumurthy, 2004).

4 Profitability of technical analysis: measures and results

The evidence concerning the profitability of technical currency analysis tends to be inconclusive. From a theoretical point of view, this is perhaps unsurprising, since if technical analysis was *never* profitable, its widespread use (see Section 2) would be hard to understand; if, on the other hand, technical analysis was *always* profitable, it would perhaps imply that the foreign exchange market is inefficient to a degree that many economists would not find credible.

Indeed, the EMH does not imply in this respect that returns to applying a technical trading strategy have to be zero. Rather, efficient markets "rule out the possibility of trading systems based only on [current and past] information [having] expected profits or returns in excess of equilibrium expected profits or returns" (Fama, 1970, p.385). In this context, equilibrium expected returns must be calculated after allowing for a reasonable return to risk and after allowance for transactions costs.[14]

In assessing the profitability of technical analysis, therefore, three methodological aspects have to be addressed carefully. First, any examination should define appropriate alternatives, i.e. on the one hand the technical analysis strategies and on the other hand a

---

their decision making. See Sager and Taylor (2006) for a comprehensive analysis of the structure of the foreign exchange market.

[13] It is possible that order flow might better be interpreted as fundamental rather than as technical information since, although it is clearly not on the list of standard macroeconomic fundamentals, it may in some sense embody the net effect of fundamental influences on the foreign exchange market (Lyons, 2001; Evans and Lyons, 2005b). Nevertheless, we rely here on studies in which order flow forms a third category and which may to some extent represent the current perception of order flow by foreign exchange professionals (Henderson, 2002; Gehrig and Menkhoff, 2004).

[14] It may also allow for tax payments, where tax treatment differs across investor groups.

strategy relying on the EMH. Important features of this comparison must include transaction costs and interest rate carry costs.[15]

Second, the issue of statistical significance has to be tackled. Independently of the distribution of exchange rate returns, there must always exist a technical analysis strategy that is able to exploit characteristics of the time series in any particular sample. Thus, it is not profitability *per se* that is interesting but the possible significance of the result that challenges the EMH.

Third, it is probably the form of risk consideration—an essential element of Fama's "equilibrium expected profits"—that divides advocates and opponents of technical analysis in the interpretation of their empirical work.

If one compares the overview of earlier studies in Table 4 with the three requirements just mentioned, it becomes clear that these studies are all characterized by shortcomings to a greater or lesser extent: many of them examine only one currency, some do not consider all kinds of costs and most are handicapped by a short period of investigation which does not allow for appropriate out-of-sample calculations. Thus, only the studies of Dooley and Shafer (1983) and Sweeney (1986) have been consistently cited in the literature (see e.g. Gencay, 1999; LeBaron, 1999; Neely, 2002; Olson, 2004).

It is interesting to note that most of the stylized facts that can be drawn from profitability examinations are already found in this early literature (Table 4) and that they are supported by later studies (e.g. Surajas and Sweeney, 1992; Menkhoff and Schlumberger, 1995; Pilbeam, 1995; Neely, 1997; LeBaron, 1999; Saacke, 2002). They can be gathered together here as Stylised Facts 4, 5 and 6:

Stylised Fact 4 (SF4): *The consideration of transaction costs and interest rate costs actually faced by professionals does not necessarily eliminate the profitability of technical currency analysis.*

Stylised Fact 5 (SF5): *Technical analysis tends to be more profitable with volatile currencies.*

[15] It must also constitute a study of profitability from an *ex ante* rather than an *ex post* perspective, so that there is perceived profit from gathering and utilising information in a superior fashion. This is important because it could be argued that, in equilibrium, there should be no gain from utilising superior information since such information would already be embodied in market prices. If this were the case, however, traders would presumably not bother to gather costly information, in which case it is difficult to see how the information would be imparted into market prices at all, so that the proposed "no-profit-from-costly-information equilibrium" implies a contradiction and so cannot in fact be an equilibrium. This is the so-called Grossman-Stiglitz paradox, and in the resolution of this paradox, both Grossman and Stiglitz (1980) and Cornell and Roll (1981) have shown that a sensible financial market equilibrium must leave some incentive for costly information acquisition and analysis.

Stylised Fact 6 (SF6): *The performance of technical trading rules are highly unstable over time.*

Evidence on *SF4*—the profitability of technical trading rules after allowance for transactions costs and interest rate carry—is provided by, among others, Cornell and Dietrich (1978), Sweeney (1986), Schulmeister (1987), LeBaron (1999), Saacke (2002) and Neely, Weller and Ulrich (2006). Studies supporting the hypothesis that technical trading rules are more profitable for currencies experiencing relatively higher volatility (*SF5*) include Cornell and Dietrich (1978), Dooley and Shafer (1983), Lee and Mathur (1996) and Neely and Weller (1999). Work suggesting that technical trading rule performance is unstable over time (*SF6*) include Logue, Sweeney and Willett (1978), Dooley and Shafer (1983), Menkhoff and Schlumberger (1995), LeBaron (2000), Dueker and Neely (2005) and Neely, Weller and Ulrich (2006).[16]

The rapidly growing empirical literature on the profitability of technical analysis in the foreign exchange market that has appeared since the late 1990s has, if anything, further substantiated these older stylized facts (see, e.g., Park and Irwin, 2005). In addition, it is possible to discern a number of developments among the more recent literature.

First, a major methodological innovation has been the introduction of the bootstrap approach addressing the problem of insignificant evidence (Levich and Thomas, 1993; LeBaron, 1999, 2000; Osler, 2000, 2003) and, more recently, the introduction of methods for testing for potential data-snooping bias (Park and Irwin, 2005; Qi and Wu, 2006).

Second, the range of technical analysis tools and trading rules considered has been increased far beyond filter rules, moving averages or point-and-figure indicators, and now includes the possible psychological barriers of round figures, the closely related issue of support and resistance levels (De Grauwe and Decupere, 1992; Curcio and Goodhart, 1992; Osler, 2000, 2003, 2005) or of momentum-based strategies (Okunev and White, 2003).[17]

Third, the longer span of data available for the floating rate period since the early 1970s has stimulated the question as to whether profits from technical analysis are declining

[16] As an anonymous referee has pointed out, the evidence for the instability of technical trading rules should be interpreted with care, however, since exchange rate returns are noisy relative to sample length, tests for unknown structural breaks have notoriously low power and test for structural breaks at known breakpoints are subject to data snooping bias. Moreover, the popularity of technical analysis may be sustained not by its *consistent* performance but by its *perceived* performance across various prominent episodes and instability in performance over time is also a characteristic of fundamentals-based exchange rate models (Cheung, Chinn and Garcia Pascual, 2005).

[17] The technical trading rules that have been examined in this literature include those based on head and shoulders patterns (Chang and Osler, 1999; Lucke, 2003), candlestick formations (Fiess and MacDonald, 2002), neural networks (Gencay, 1999), genetic programming (Neely, Weller and Dittmar, 1997; Neely and Weller, 1999, 2001), Markov switching models (Marsh, 2000; Dueker and Neely, 2005) and real-time trading models (Gencay et al., 2003).

over time. There is indeed evidence that the foreign exchange market has become more efficient over time in the sense that the application of traditional moving average rules, that was shown to be profitable for the 1970s (e.g. Logue and Sweeney, 1977; Cornell and Dietrich, 1978; Dooley and Shafer, 1983; Sweeney, 1986), became much less profitable in the 1990s (LeBaron, 2000; Olson, 2004), even after allowing for a reduction in transactions costs over time (Neely, Weller and Ulrich, 2006). Although significant evidence of profitability—albeit on a reduced level—remains and may even have been increasing during recent years in euro-dollar trading (Park and Irwin, 2005; Schulmeister, 2005). Also, there may be more complex forms of technical analysis that did not become less profitable over time (e.g. Okunev and White, 2003; Neely, Weller and Ulrich, 2006).[18]

Fourth, there have been attempts to avoid potential selection bias by letting actors state their preferred rules prior to any profitability analysis (Allen and Taylor, 1990; Curcio and Goodhart, 1992, 1993; Osler, 2000).

Fifth, studies have explored the relation between non-linear exchange rate modelling and technical analysis (Clyde and Osler, 1997; Fiess and MacDonald, 1999; Kilian and Taylor, 2003; De Grauwe and Grimaldi, 2006, 2006a; Reitz and Taylor, 2006).

Sixth, stimulated by the apparent success of longer-term exchange rate modelling via a Markov switching approach (Engel and Hamilton, 1990), studies have found some links between regime switches and technical trading rules (Dewachter, 1997, 2001; Vigfusson, 1997). However, profitability does not seem to be better than for simple moving average rules (Dueker and Neely, 2005) although an advantage may be gained by the fact that profits remain more stable over time (Neely, Weller and Ulrich, 2006).

Finally, some studies (Curcio et al., 1997; Osler, 2000, 2003; Neely and Weller, 2003; Kozhan and Salmon, 2006) have examined the profitability of technical analysis on a very high-freqency (intra-day) basis, with mixed results.

On balance, however, the literature on the profitability of technical trading rules tends to support the existence of significant profits to be had by employing these rules in the foreign exchange market (see also Park and Irwin, 2004). Of course, this in itself raises a sample selection bias issue, since it is well known that positive results are generally much easier to report than negative results. In particular, these studies may be subject to "data snooping" (White, 2000). Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection, so that the possibility arises that any satisfactory results obtained may simply be due to chance rather than to any merit or skill inherent in the

[18] Similar results are reported by Hsu and Kuan (2005) for stock markets, providing support to the interpretation of Neely, Weller and Ulrich (2006) that markets may need time to become aware of and then to arbitrage away profit opportunities generated by technical trading rules.

method yielding the good results. White (2000) develops a bootstrap simulation technique—the "reality check"—for examining whether it is inherent skill or pure chance that leads to the best rule being chosen out of any given universe of rules. Intuitively, a reality check involves replicating, by Monte Carlo methods, many artificial data sets that in some sense match the properties of the original data sets, and testing the various trading rules for profitability on each data set. If there is a tendency for the same rule to be selected as the most profitable for each data set, then this suggest that it really is a good rule; if there is no tendency to select that particular rule for each of the artificial data sets, then this indicates that it was selected as the most profitable rule in the original data set purely by chance.[19]

The first application of White's reality check to technical trading rules in the foreign exchange market is due to Qi and Wu (2006). These authors examine a large number of technical trading rules and apply them to daily data on seven dollar exchange rates over the period 1973-1998. The technical rules are various calibrations of four classes of rules: filter rules (buy or sell a currency if it moves more than a certain percent from its most recent high or low); moving average rules (as discussed above); support and resistance rules (buy or sell a currency when it breaks above or below the maximum or minimum level, the resistance level, over a stipulated recent period); and channel breakout rules (but or sell a currency when it breaks out of a channel, defined as occurring when the high price of a foreign currency over the previous *n* days is within *x* percent of the low over the previous *n* days). Using standard tests, Qi and Wu's results indicate significant profitability of moving average and channel breakout rules for seven dollar exchange rates. They then apply White's (2000) reality check bootstrap methodology to evaluate these rules and to characterize the effects of potential data-snooping biases. They find significant profitability at the one percent level for all seven currencies even, after data-snooping biases (as well as transactions costs) are properly taken into account (Park and Irwin, 2005, find a similar result for euro and yen futures). Moreover, employing the Japanese yen or the German mark as a vehicle currency (instead of the US dollar) yields even stronger results.

[19] An anonymous referee has pointed out a number of issues that may be raised with respect to White's reality check. In particular, while the reality check is clearly an improvement over earlier approaches that ignored data-snooping bias, the group of trading rules making up the universe within which the reality check is carried out must still be chosen and that brings back the danger of data snooping in a different guise. Indeed, there may even be a systematic bias involved as researchers may, consciously or unconsciously, rely on rules that have been implicitly tested on similar data in previous research. Moreover, merely adding a large number of poor rules into the reality check universe will tend to raise the critical values for a given nominal test size while the performance of the benchmark trading rule does not change. An alternative approach would be to carry out an ex ante search for profitable trading rules using artificial intelligence such as a genetic algorithm that "learns" trading rules and applies them, as in the equity-market study of Allen and Karjalainen (1999), although this approach would also potentially be subject to sample-selection bias. Alternatively, one can perform true out-of-sample tests by retesting rules that have found to be profitable in earlier studies—as for example in LeBaron (2000) or Neely, Weller and Ulrich (2006).

Even if the existence of significantly profitable technical trading rules can be established, however, there is still the possibility that all that is being measured is a risk premium, so that the risk-adjusted returns from the rule would on average be non-positive. Table 4 revealed already that earlier studies usually ignored this issue but more recent studies have elaborated on it (see Table 5). The pioneering attempt in this respect is Cornell and Dietrich (1978) who suggest a risk adjustment according to the international capital asset pricing model (ICAPM). Their empirical realization is limited, however, by practical constraints: first, the world portfolio is proxied by a US market stock index (the S&P 500) and, second, they generally calculate the beta of foreign currencies with this index rather than the beta of currency positions that result from technical trading rules (for the latter see e.g. Taylor, 1992, with the same result).[20] Nevertheless, their very low beta estimates suggest that investing in foreign currency provides a good hedge for an investor whose portfolio is primarily centred on US stocks (see also Neely, 1997).

The first study systematically integrating risk-adjustment into the empirical examination of certain rules, however, was due to Sweeney (1986). This study characterizes a quite different approach to that of Cornell and Dietrich (1978), as it compares trading rules based on technical currency analysis rules to buy-and-hold strategies. If, for example, deviations from uncovered interest rate parity (the condition that the expected excess return, net of interest rate carry, from buying and holding foreign currency should be zero) simply represent risk premia, then a possible implication is that apparently profitable technical trading rules are simply picking up these risk premia. Sweeney indeed calibrated his work under the assumption of a constant risk premium, i.e. the average return on foreign exchange holdings is adjusted by the foreign-domestic interest rate differential. Then the excess return on following the technical analysis rule, i.e. gross return minus return from buy-and-hold, is adjusted by the share of days that the trading rule is invested in foreign currency and has thus to earn a risk premium. According to this procedure, Sweeney did not find a risk-based explanation for excess returns. Levich and Thomas (1993), applying a similar methodology, found a similar result.

However, these results may be questioned on at least two grounds. First, it is not clear why one should expect a positive risk premium for investing in one currency in a bilateral exchange rate as this implies that investment in the second currency (or a short position in the first currency) earns a negative risk premium.[21] Second, the assumption of a constant foreign exchange risk premium is not a very realistic one (Taylor, 1995). The first study to relax this

[20] From today's perspective, the choice of a US portfolio may seem less of a shortcoming, taking account of the well-documented preference of investors for home assets (Lewis, 1999).

[21] We thank two of the anonymous referees for encouraging us to make this argument.

assumption in the context of technical trading rules was Taylor (1992), who allows for a time-varying risk premium in the form of a first-order autoregressive process. Parameter values of this process, justified by results from other studies, are used to enter into a pricing model. For several combinations of parameter values, hundreds of time series are then simulated on which technical analysis rules are evaluated. It is found that there does not seem to be a reasonable constellation of parameters for the time-varying risk premium which would be needed to explain observed returns as a compensation for risk (see also Okunev and White, 2003). On the other hand, all that this evidence may be revealing is that the wrong parameterisation of the risk premium was assumed.

A much more extensive approach in deriving time-varying foreign exchange risk premia in this context is adopted by Kho (1996). He relates possible excess returns to a world stock portfolio (the MSCI index) in a conditional ICAPM framework. Within his framework, there are basically three factors which are assumed to determine world excess returns: interest rate differentials against the US dollar, the conditional variance of world excess returns and a moving average term. The empirical work uses econometric models in which the conditional variance is allowed to affect the conditional mean (i.e. GARCH-m models) in order to calculate expected risks. Kho finds that much of the technical analysis returns can indeed be explained as compensation for the high risks involved.

The above approaches to incorporate risk into profitability measurement implicitly need a benchmark model of asset pricing in equilibrium. Obviously, the ICAPM is most popular in this respect although empirical finance may tentatively prefer multi-factor models, such as the Fama and French (1996) approach. From a theoretical point of view consumption-based asset pricing seems more advantageous to the CAPM (Cochrane, 2005). However, neither of these approaches has been applied to the foreign exchange market.[22] Given the failure in identifying meaningful time-varying risk premia in international finance in general (Taylor, 1995), this shortcoming may be excusable. This lack of knowledge has, moreover, fuelled other ways of addressing the riskiness inherent in the use of technical analysis.

Some studies circumvent the problem of measuring the world portfolio and deriving risk premia. Instead, they directly compare the return-risk-profile of a speculative currency portfolio to a benchmark portfolio by using the ratio of annualised excess returns (relative to a benchmark strategy) to the standard deviation of those returns, i.e. the Sharpe or information ratio (Sharpe, 1966). Alternative benchmarks in this respect are either a buy-and-hold currency strategy (e.g. Menkhoff and Schlumberger, 1995) or the return from holding a broad portfolio index such as the market index (e.g. Neely, 1997; Chang and Osler, 1999; LeBaron,

[22] It is interesting to note in this respect that these more advanced approaches are also confronted with evidence that questions their explanatory power (Lewellen, Nagel and Shanken, 2006).

2000; Saacke, 2002).[23] The results of these studies show higher risk-adjusted returns to technical analysis rules than to the benchmark portfolios.[24]

The popular Sharpe or information ratio (IR) has its own problems, however, when it is used as a criterion by which to measure the performance of trading rules. Suppose that the mean excess return of the trading rule over a period of T years is $\overline{\alpha}$, with standard deviation σ. Then the IR will be defined as

$$IR \equiv \frac{\overline{\alpha}}{\sigma}.$$

Now, it can easily be shown that τ=√T ×IR is approximately equal to a *t*-ratio for a test of the hypothesis that the excess return is zero.[25] A common benchmark for a "good" trading rule in the finance industry in general is an IR of 0.5 (see, e.g. Grinold and Kahn, 2000). But this means that an IR of 0.5 must be sustained over about eleven years before the trading rule can be said to have generated excess returns significantly greater than zero at the 5 percent significance level, since this would give a value of τ (==√11 ×0.5=1.658,) greater than the critical value for a one-sided test at the 5 percent level (i.e. 1.645). Suppose that a trader selects a certain rule because it has an IR of 0.5 according to a "backtest" with ten or more years of data. As we discussed earlier, there is a strong likelihood that the rule will be subject to data-snooping, and a true out-of-sample test would require that the trader keeps the rule and monitors its performance over the ensuing ten or eleven years or so—which is a very long time in the financial markets.

This picture changes, however, if one measures risk not in the traditional sense of the variability of returns but if one tries instead to integrate the professionals' perception of risk as relating to relative performance in comparison with the market (see e.g. Goodhart, 1988, p.457). Here, *SF6* comes into play, namely that profitability is unstable over time. In summary, applying technical analysis involves a high probability of making "wrong" decisions, i.e. performing below the market, at least during some periods (see e.g. Silber, 1994, p.44; Neely, 1997). Thus, Menkhoff and Schlumberger (1995) suggest addressing the risk inherent in using technical analysis by focusing on the monthly difference between the rules' profitability performance and a buy-and-hold performance (this may be understood as a

---

[23] These alternative benchmarks are second-best solutions adopted from the equity market literature. Thus, the buy-and-hold benchmark implicitly uses a national, one-sided perspective whereas trading rules in foreign exchange are typically symmetric with respect to the two currencies involved. Regarding the index benchmarks, they implicitly assume that the trading rule would be an alternative to another investment. Accordingly, such benchmarks should not be taken literally.

[24] In this vein, Dewachter and Lyrio (2005) find that the application of moving average rules can provide a significant return to investors.

[25] This result is independent of the distribution of excess returns and follows from the Central Limit Theorem, which states that whenever a random sample of size T is taken from any distribution with mean α and variance ς^2, then the sample mean will be approximately normally distributed with mean μ and variance ς^2/T.

form of myopic loss aversion, see Benartzi and Thaler, 1995). Due to the high instability of technical analysis' returns, the "excess return"—as shown by raw returns or by a Sharpe ratio criterion—ceases to be significant at the 5% level.

In a recent paper, Charlebois and Sapp (2006), using daily data on dollar-mark over the period 1988-1998, find that moving-average trading rules generate significant excess returns and that the excess returns increase when information is included on the open interest differential on currency options (i.e. the net difference between the cumulative value in dollar terms of all put options that are still active on a given day less the cumulative value of all active call options). They interpret this as partly reflecting risk premia and partly as reflecting extra fundamental information that is reflected in options prices, since options may be the instrument of trading of choice of more informed traders because of the leverage advantage provided (Easley, O'Hara and Srinivas, 1998). Some evidence supporting this view is provided by the fact that when the authors exclude the fifty largest absolute daily returns, all of the trading rules incorporating the open interest differential become less profitable (implying that the excess returns of technical trading rules to some extent reflect compensation for risk), but many of them nevertheless remain strongly profitable.

In summary, looking at the last column of Table 5, where risk-adjusted profitability is displayed, the majority of studies conclude that the profitability of technical currency analysis holds in a risk-adjusted sense. Going more into detail, there is, first, evidence that time-varying risk premia might explain some of the excess return of technical analysis but not all or even most of it (Taylor, 1992; Kho, 1996).[26] Furthermore, even the correct determination of appropriate risk premia is questionable with the present state of knowledge. A second line of argument is that it is perhaps possible to explain some of the excess returns using a measure of risk as perceived by market participants. Indeed, the available evidence indicates that technical analysis is quite risky in this respect.

5 Explaining the continued use of technical analysis in the foreign exchange market

Technical analysis is an important tool in real-world decision making in foreign exchange markets (*SF1*, *SF2* and *SF3*). In addition, it appears that applying certain technical trading rules to volatile foreign exchange markets over a sustained period may lead to significant positive excess returns, although it is not clear that the performance of these rules is stable

[26] One must admit, however, that there is not much guidance as to whether the measures of risk premia used in the empirical literature are fully convincing from a theoretical point of view. For example, Taylor's (1992) AR(1) risk premium model may simply be too restrictive, while—as an anonymous referee has commented—the Kho (1996) study is based on a limited sample and has not to date been replicated for other currencies or sample periods.

over time or that the excess returns earned significantly outweigh the associated risk premia (*SF4*, *SF5* and *SF6*).

There remains a need for further explanation of the continued and passionate obsession of foreign exchange professionals with technical analysis, however, as profitability studies have not to date arrived at a clear verdict. The organizing idea here is to allow explicitly for heterogeneous agents and asymmetric information in the foreign exchange market, which makes market efficiency a more complex concept. It may, however, be reassuring in this context that this complexity can indeed by rooted in Fama's (1970, p.388) seminal paper on financial market efficiency, as he discusses "disagreement among investors about the implications of given information" as a potential source of "inefficiency". So, in what way may disagreement (i.e. heterogeneity) help in resolving our puzzle? We group the various explanations that have been suggested into four positions, which we shall briefly describe before we relate them to rational behaviour of agents and efficient markets (see Figure 3 for an overview).

If one follows the traditional understanding of the EMH and regards foreign exchange markets as at least weakly efficient in the sense of Fama (1970)—i.e. in the sense that significant profits cannot be generated using forecasts based on past price movements alone—then one would assess the use of technical analysis as evidence of irrational behaviour. This is the first explanation for the continued use of technical analysis in the foreign exchange market.

However, the assumption that most professionals in the market behave consistently irrationally does not fit the EMH either: according to the EMH, they should quickly be driven out of the market as they make losses at the expense of rational traders. But if there is an important set of foreign exchange market participants who are not directly interested in generating profit but nevertheless have a significant influence on the market, then these participants may generate profit-making opportunities for technical analysts over sustained periods of time, allowing them to survive in the market. One such group that has been proposed in this context is comprised of the major central banks, and the behaviour of central banks in intervening in the foreign exchange market has been posited as a second explanation for the persistence of technical analysis.

A third position is that if it takes time for the effects of economic fundamentals to feed through fully into market exchange rates, then technical analysis may serve as a means of detecting these kinds of influences earlier than would otherwise be the case.

Fourthly and finally, it has often been argued that financial prices may not only reflect the information from fundamentals but also influences from other sources, such as the influence of noise traders or the self-fulfilling influences of technical analysis itself.

Among these four explanations, it is only the first that directly refers to irrational behaviour of agents: either the users of technical analysis are simply irrational and will be driven out of the market (as suggested by Friedman, 1953) or they systematically underestimate risk (as suggested by De Long et al., 1990). The other three explanations do not rely on technicians' irrationality but on Fama's (1970) argument that not all market participants need to interpret all information at the same time in the same way.

With regard to the foreign exchange intervention-explanation, it would be the central bank that distorts markets and technical traders profit from this "inefficiency". Regarding the third explanation, technical analysis is seen as an instrument via which to learn about the revelation of fundamentals that cannot be recognized from observing fundamentals directly.[27] Here, neither technical traders nor the market need be inefficient except according to a very strict form of the EMH requiring that market prices should reflect new information *instantaneously*; in the real world, it takes time to learn and technical analysis may be one method of learning. Finally, in the fourth strand of explanations, there are not-fully-rational traders in the market who have price impact and whose behaviour can be detected and exploited by technical analysis. Obviously, in this case markets are not efficient and technicians who are rational in the sense of exploiting all available information for trading purposes (whether it is information about fundamentals or non-fundamental influences) will profit at the expense of noise traders who are irrational in the sense of *not* using all available information.

It seems noteworthy that in the three latter explanations discussed here the commonality is that there are price-relevant influences that cannot be addressed by conventional fundamental analysis, either because the central bank intervenes or because fundamentals cannot be observed or else because non-fundamentals impact on prices.[28] By using these pieces of "information" technical analysis does not necessarily yield excess returns.

We review below the available empirical evidence with respect to each of these four positions.

5.1 Technical analysis as reflecting irrational behaviour

The charge of not-fully-rational behaviour on the part of those applying technical analysis is probably the most common position in explaining its use, since in its reliance on extrapolation

[27] We agree with an anonymous referee that order flow seems to have a fundamental component and appears to be related to movements in fundamentals (Evans and Lyons, 2005b).

[28] It is thus only the third explanation that requires the presence of outright non-fundamental forces in the market. Intervention itself, referring to the second explanation, may react on non-fundamental prices or create

and/or visual pattern recognition, technical analysis is inconsistent with weak efficiency of the foreign exchange market. However, as mentioned earlier, this position has the paradoxical implication that the market is in fact not efficient since technical analysis is so widely used in the market (*SF1*). Thus, there must be more subtle reasons for using technical analysis rather than just an outright lack of rationality. In effect, there seem to have been three arguments put forward in the literature.

First, that the irrational behaviour may be of a largely temporary nature.

Second, that it may be the case that users of technical analysis systematically underestimate the risks involved in its use.

Third, that the application of technical analysis may in fact be a form of marketing or "window dressing" on the part of financial institutions in order to impress and attract less-informed clients.

Regarding the first argument, concerning temporarily irrational behaviour, one would need information about the behaviour of participants in the time-series domain to test directly whether behaviour changes over time—this data is not available so far. An alternative is to test the cross-sectional implications of this approach, for example that traders relying on technical analysis tend to be less experienced and will in some sense learn to use fundamental analysis as their experience grows over time. Learning means here the same as learning the "right model", i.e. the lesson of avoiding technical analysis in the future. Another implication seems to be that not-fully-rational behaviour will not lead to market success, so that chartists do not reach senior positions as often as others. Finally, non-rationality may be a consequence of a lower level of education, since it may be argued that technical analysis does not require any level of economic understanding but is—quite the contrary—easily understandable on an intuitive basis.

These three implications of the assumption of temporary irrationality on the part of traders using technical analysis have been tested with survey data of Gehrig and Menkhoff (2006). The details, given in Table 6, reveal that those market participants who prefer the use of technical analysis are not, in fact, characterized by symptoms of a possibly sub-optimal behaviour (see also Menkhoff, 1997; Cheung and Wong, 1999; Cheung, Chinn and Marsh, 2004).

This leads to the next argument, put forward by De Long et al. (1990) in the more general context of noise traders, that the application of technical analysis may be related to an underestimation of the risk involved by its users. Again, there is no direct evidence available which could inform about risk preferences and risk perception of chartists. Moreover, the

---

them. The third explanation may be related to non-fundamental prices when market participants are affected by a preference for certain figures.

studies examining risk-adjusted profitability do not come to a unanimous conclusion (see Section 4). The only study that directly compares the consequences of relying on technical rather than fundamental analysis is that of Curcio and Goodhart (1993). In their experiment the profit of technical traders and of fundamentalists was similar but the volatility was lower for the users of technical analysis. This might indicate, therefore, that technical analysis can in fact serve as a risk-reducing instrument. As this is, however, only a single study, the significance of this result should not be overstated.

Fortunately, there is another piece of evidence which can be drawn from the form of technical analysis that is preferred. Both studies asking this question come to the same conclusion that trend-following forms dominate rate of change indicators (see Taylor and Allen, 1992, Table 1A; Lui and Mole, 1998, Table 4). If one assumes that most people would regard “going with the wave” as less risky than betting against it, this preference of available instruments does not indicate risk-loving behaviour.

Overall, therefore, the evidence presented is unavoidably thin. Nevertheless, available information does not support the notion of chartists being a selection of people who underestimate risk in general.

There is, finally, a third argument in favour of not-fully-rational behaviour on the part of technical traders—the marketing argument. The claim here is not that technical analysis can provide any useful information in forecasting but that it generates buy and sell signals which translate into fee and commission income for financial intermediaries (see e.g. Sylla, 1992, p.343). This view may characterise the motivation of those selling technical analysis, but it does not explain why others buy such services. If technical analysis were particularly popular with small investors or other less professional market participants (e.g. “day traders”), this argument would come close to the first argument discussed above, i.e. that of sub-optimal behaviour. Unfortunately, there is no evidence that small investors are in fact particularly heavy users of technical analysis, although it is known that a large number of professionals adhere to this tool. In addition to the evidence presented in Section 3 it can be said that according to the survey of Taylor and Allen (1992, Table 1), most institutions subscribe to some form of external chartist advice. Moreover, about 25% employ an in-house technical analyst in comparison to 39% who employ an in-house economist (ibid., Table 2).

In summary, the evidence regarding the not-fully-rational behaviour position in explaining the use of technical analysis is mostly quite indirect. Nevertheless, it is interesting to note that available information points against rather than in favour of this position.[29]

[29] Despite this interpretation of the available systematic evidence we do not wish to claim that there is *no* irrationality in the market (Oberlechner, 2004; Oberlechner and Osler, 2006).

5.2 Technical analysis as exploiting the impact of central bank interventions

As the central bank is not part of the regular market process and, in particular, foreign exchange intervention is not generally motivated by profit considerations, the process of central bank intervention in the foreign exchange market may provide an explanation as to why financial markets are actually efficient although excess returns can be earned. This idea was formulated long ago—see, for example, Dooley and Shafer (1983, p. 65), Levich (1985) or Sweeney (1986)—but it had not been tested in a rigorous way until quite recently.

The seminal paper in this respect is the study by LeBaron (1999). He applies a simple moving average rule to a fourteen-year period (1979 to 1992) of daily as well as weekly time series of D-Mark/US-Dollar and Yen/US-Dollar exchange rates. This rule generates considerable returns—of the order of more than 5% per year (LeBaron, 1999, Table 4). LeBaron calculates, however, the effect of removing days when official foreign exchange interventions took place. The result is that the formerly highly profitable technical analysis rules diminish in attractiveness (LeBaron, 1999, Figure 2). This indicates that intervention "has something to do with the observed predictability" (ibid., p.137). In order to address the issue of a possible third factor in this analysis, LeBaron (1999) undertakes several checks to investigate the existence of common factors that might drive interventions and profitability of technical analysis at the same time. One finding is that periods of highest expected volatility (calculated using GARCH models) are not those of highest profitability of the moving average rules.

The thrust of this literature suggests that official interventions may distort the relationship between standard fundamentals and exchange rate movements and thereby disadvantage fundamentals-oriented traders while possibly favouring technical traders, for example if the intervention creates trends in the exchange rate or support and resistance levels.

LeBaron's (1999) analysis has been extended by Saacke (2002). Saacke not only considers US data but also interventions by the Deutsche Bundesbank. Moreover, this study covers two additional years and considers a wide range of technical analysis rules and confirms LeBaron's findings.

Other studies that make similar arguments concerning the influence of central bank intervention on technical analysis profitability include Silber (1994) and Szakmary and Mathur (1997). Silber (1994) generally links markets where technical analysis is profitable with the fact that these are the markets where central banks intervene. Szakmary and Mathur (1997) examine five major foreign exchange markets but rely on the IMF's International Financial Statistics to infer the degree of intervention from data on foreign exchange reserves. These monthly figures cannot reveal higher frequency interventions and are influenced by nuisance components, such as revaluations or interventions in third currencies. Interestingly, however, they nevertheless reach basically the same conclusion as LeBaron (1999).

This interpretation—i.e. that central bank intervention may be the source of the profitability of technical analysis—has been cautiously questioned by Neely (1998). He stresses the point that, due to LeBaron's methodology, most of the profits from technical analysis rules occur concurrently with intervention operations (see Neely, 1998, p.7f.). If official interventions tend to occur when markets are trending, this would also explain the findings of LeBaron and others. In particular, if intervention days are those where markets move heavily (and might possibly move even more strongly without interventions), then interventions and technical analysis profitability may be positively correlated. The decisive step necessary to test this competing interpretation is the use of intradaily as opposed to daily data.

Neely (2002) has performed this task by combining several sources of daily data available at different times during the trading day. He checked the timing of technical analysis profitability and intervention for five exchange rates, mostly over the period from 1983 to 1998. Neely finds that "intervention reacts to the same strong short-run trends from which the trading rules have recently profited" (Neely, 2002, p.230). The result is confirmed for a high-frequency analysis of Bundesbank interventions (Frenkel and Stadtmann, 2004). It is also compatible with Neely and Weller's (2001) result on daily data, namely that their genetic programming rules are most profitable on the day *before* interventions take place.[30] Moreover, information about central bank information does not increase profitability.

In a recent study using daily data on the mark-dollar exchange rate and foreign exchange intervention data from the Federal Reserve and the Bundesbank, Reitz and Taylor (2006) analyze the interaction of chartism, fundamentalism and central bank intervention and provide evidence that intervention is most likely to occur and to be effective *after* a period of sustained trending away from the equilibrium level suggested by purchasing power parity. They argue that this is evidence of the "coordination channel" of intervention effectiveness, which has been put forward by Taylor (1994, 2004) and Sarno and Taylor (2001a). According to the coordination channel, if technical analysts are capable of driving the exchange rate away from its fundamental equilibrium level over a sustained period, then fundamentalist analysis will not be profitable and fundamentalists will lose credibility in the market, or confidence in the fundamentals. Hence, fundamentalists will reduce their trades based on

[30] One reason that technical analysis may be profitable before interventions was revealed by Peiers (1997), indicating that one bank had superior forecasting performance with respect to later interventions. It seems plausible that this bank had an information advantage, so that these profits may be due to private information—this would not reject market efficiency in its semi-strong form, i.e. relying on the use of publicly available

fundamental analysis and the exchange rate will tend to stick away from (and perhaps still trending away from) the fundamental equilibrium. (This is an example of the "limits of arbitrage" effect, as suggested in a more general setting by Shleifer and Vishny, 1997.) When this occurs, the central bank may at some point intervene publicly in the hope that the intervention will act as a coordinating signal to fundamentalists to enter the market at the same time and so return the exchange rate to its fundamental equilibrium level. To the extent that fundamentalists rally to the central bank's clarion call, the intervention will then be effective. Using a nonlinear microstructural model of exchange rate behaviour, Reitz and Taylor (2006) find evidence supportive of the existence of a coordination channel of intervention effectiveness.

The coordination channel therefore provides a rationale as to why intervention, the use (or profitability) of technical analysis, and trending exchange rates may all coincide. Note, however, that the coordination channel implies that intervention may be effective *because* technical analysis is effective in generating a sustained trend away from fundamentals, not vice versa.

A final piece of evidence on the relation between intervention and technical analysis profitability is provided by Sapp (2004). He finds that market uncertainty—measured by spread and volatility—is high before interventions and lower afterwards. This provides an economic rationale for interventions (see also Chaboud and LeBaron, 2001) and indicates that profits earned by technical analysis during these periods may be a compensation for risk.

5.3 Technical analysis as a method of information processing

Another explanation for the continued use of technical analysis is that it is in fact simply an instrument for processing and assimilating market information that is contained in exchange rates. The question concerning how fundamental information is imparted into financial prices has long been a field of debate. If one leaves the macroeconomic level and goes down to the actions of individual market participants at the microstructural level, it becomes clear that it will often be single entities or limited groups that recognize or correctly interpret fundamental changes earlier than others. These others may for some time interpret the actions of the better informed group as liquidity or noise trading, so learning takes time. Assuming that the fundamentally correct view succeeds in the end implies that there exists an intermediate period during which exchange rates move from the "incorrect" to the "correct" level. Hellwig

---

information. Probably, this finding should not be generalized to other banks as the persistent forecasting power could not be found for other situations (Sapp, 2002; Dominguez, 2003).

(1982) was among the first to model this process and to note that it allows less informed traders to infer information from observing past price movements. Thus, on this argument, inferring future price movements from past price movements, as in technical analysis, may not be so irrational after all (Treynor and Ferguson, 1985; Brown and Jennings, 1989).[31]

The decisive point in this connection, however, is whether or not this reasoning has any resemblance with the real-world conditions of foreign exchange markets. Some evidence that this is indeed the case is provided by Sager and Taylor (2004) and Melvin, Sager and Taylor (2006), who show, using five-minute data on dollar-sterling and dollar-euro exchange rates, that there is an upward shift in exchange rate volatility following the interest rate announcements of the European Central Bank and the Bank of England, suggesting a period of learning. Earlier work supporting this notion includes Goodhart's (1988) examination of exchange rate changes in reaction to major fundamental news, which he assesses as initial under-reaction (see Evans and Lyons, 2005a). Further, a number of authors have recently analysed the high-frequency reaction of foreign exchange markets to news announcements more generally, and this work reveals that markets do react very quickly: most price reaction to scheduled news is in the form of an immediate jump (Andersen et al., 2003). Unfortunately, however, these price changes explain only a marginal fraction of overall price variability and even after such marked jumps volatility remains persistent for at least an hour—indicating that much more is going in the market.[32] Over longer horizons, by contrast, it is known that exchange rates converge towards fundamental values (see, e.g. Mark, 1995; Lothian and Taylor, 1996).

Taken together, there emerges from this evidence a pattern whereby exchange rates tend to react quickly but nevertheless may under-react on the announcement of fundamental news. Despite their reversion to the fundamental value over longer horizons, there is an intermediate period where price changes are imperfectly understood. The role of technical analysis—in the form of trend-following signalling rules (e.g. moving average rules)—may therefore be to detect emerging shorter-term trends. There is some empirical evidence consistent with this interpretation.[33]

[31] Nevertheless, there is always the possibility—as an anonymous referee has pointed out—that information processing can sometimes be linked to the 'simple heuristics' side of the psychology literature (e.g. Gigerenzer and Todd, 1999).
[32] An anonymous referee has pointed out that the limited power of such studies to explain exchange rate behaviour even within short intervals may suggest that other forces are at work. The role of technical analysis is unclear in this respect as it could either be used as an instrument via which to assimilate information, or itself be a factor impeding the incorporation of fundamentals into prices.
[33] There are theoretical papers, such as Barberis, Shleifer and Vishny (1998), which are capable of explaining the coexistence of short-term trends and longer-term mean reversion, although the "behavioural" elements of these models have been criticised by, e.g., Fama (1998) and Schwert (2002).

First, foreign exchange professionals show a pattern in their expectations formation that clearly resembles this stylized pattern of reaction to fundamental news. In particular, they reveal bandwagon (highly extrapolative) expectations over horizons of a week to a few months tendency towards regressive expectations over longer horizons (Froot and Ito, 1989; Frankel and Froot, 1990, 1990a; Ito, 1990). Thus, evidence that appears hard to reconcile with rational expectations may, indeed, be evidence of learning. If the learning process means for example that information is increasingly imparted into prices, then extrapolative expectations and respective technical trading rules may have a rational basis.

Second, central banks that do not explicitly intend to make profits by intervening, may nevertheless do so (Sweeney, 1997; Sarno and Taylor, 2001a). Insofar as central banks intervene, one may thus interpret their behaviour as tantamount to possessing knowledge about a true fundamental equilibrium exchange rate (or, at least, a range within which the fundamental must lie)—thus "buying low" and "selling high" to correct misalignments of fundamentals—and from which they can profit in the long run but not in the shorter term (see e.g. Saacke, 2002). This implies that fundamentals do not necessarily feed immediately into exchange rates and that technicians may try to exploit what they can learn as central banks intervene.

Third, it is a stylized fact that fundamental exchange rate models fail empirically at shorter-term horizons (Sarno and Taylor, 2002; Cheung, Chinn and Garcia Pascual, 2005). Nevertheless, recent research demonstrates the predictability of exchange rates over shorter-term horizons (see e.g. Clarida and Taylor, 1997; Clarida et al., 2003). Interestingly, exchange rate predictability appears to depend on two elements: first, the term structure of interest rates (and therefore the term structure of forward exchange rates) may capture complex expectations and, second, the regime switching process may be related to different "environments" of exchange rate determination. A fundamental interpretation of these influences seems much more difficult then the "direct" and atheoretical approach via technical analysis rules.

Fourth, technical analysis rules have most often been examined for shorter-term reactions—for example, in the case of long-short moving average combinations, in the band between five to ten days for the short moving average and up to about 150 days for the long moving average. Saacke (2002, p.464) demonstrates that this combination, both in application by market practitioners and in academic studies, appears to fit the range within which these rules are most profitable. Their application does not make sense at the very short-term end or over longer horizons. This is consistent with the position that technical analysis may be able to catch a sluggish and then overshooting shorter-term adjustment of exchange rates to fundamentals.

A further strand of the literature has focussed on the information contained in order flow that may help in understanding exchange rate movements (e.g. Ito, Lyons and Melvin, 1998; Lyons, 2001; Evans and Lyons, 2002). An important study in this connection by Osler (2003) demonstrates that customer orders can be usefully linked to technical analysis. Her study uses data on almost ten thousand conditional customer orders at a large US bank over a period of more than seven months in 1999-2000.[34] In particular, Osler constructs a limit-order book, defined as the set of currency stop-loss and take-profit orders existing at any point in time, and finds that orders are not placed randomly but concentrate near "round" exchange rate values at "big figures" or "half big figures" (such as a rate of 1.6100 or 1.6150 dollars per pound, rather than, say 1.6125 or 1.6133). The clustering of orders and the respective behaviour of three exchange rates is indeed consistent with the predictions of technical analysis that, first, downtrends tend to be reversed at support levels and vice versa and, second, that trends gain momentum when support or resistance levels are crossed.

A fruitful extension of this work, which has not so far been examined for the foreign exchange market, refers to the ability of technical analysis to locate order-book depth. In particular, in a study of order flow on the New York Stock Exchange, Kavajecz and Odders-White (2004) show, first, that support and resistance levels of technical analysis are related to price levels in the order book where liquidity is very high (echoing Osler's, 2003 results) and, second, that simple moving average indicators inform about the relative depth of the order book on one or the other side, which they call the "skewness of liquidity".

Overall, the conclusion that emerges from the research on limit-order books is that "technical analysis works because orders are clustered" (Osler, 2003).[35] More specifically, on a superficial level, it is order flow which generates the basis for the success of technical analysis but on a deeper level it is really customers' preference for round numbers in this context.[36] If decision makers' behaviour is subject to other habits and rules of thumb, then this may provide a basis for the use of other forms of technical analysis as means of exploiting movements in exchange rates generated by non-fundamental influences (see the next sub-section).

However, patterns in exchange rate movements may also reflect institutional design. Thus it is known that some technical trading rules rely heavily on very specific prices during

[34] Accordingly, this study focuses on higher frequencies than most studies covered in Section 4 on profitability which use daily data, which apply rules changing positions typically after weeks and which analyze years of trading.

[35] Another clustering, one in the time dimension, is analyzed by Lillo and Farmer (2004) for the London Stock Exchange. They find that the sign of orders, i.e. either buy or sell, is positively correlated. It seems intuitively possible to formulate technical trading rules in order to exploit such properties.

[36] An anonymous referee has commented that a feedback channel may also exist if technical analysts use "big figures" or "round numbers" in foreign exchange prices, which may motivate customers to place orders accordingly.

the trading day—in particular the opening, closing, high and low prices. One can link these prices to order flows in the sense that opening and closing prices may reveal more permanent demand and supply imbalances due to the need of many dealers to square their positions at the end of their day, whereas high and low prices may reveal a mismatch of buy and sell orders. The econometric study of Fiess and MacDonald (2002) shows that analyzing these specific prices can generate useful forecasts of exchange rates (and volatility).[37]

One could thus speculate whether similar institutionally motivated effects might be detected in the behaviour of international fund managers. It has been argued that equity market fund managers may have incentives for herding and, moreover, that there is shorter-term momentum in the returns of stocks which may be caused by herding behaviour (e.g. Grinblatt, Titman and Wermers, 1995). Further, there are indications of short-term under-reaction to news and medium-term over-reaction, so that shorter-term momentum and longer-term contrarian investment strategies appear to promise excess returns (e.g. Jegadeesh and Titman, 2001). If this behaviour translates from stock prices to foreign exchange, it may be responsible for generating shorter-term trends, i.e. momentum, which may be detected by technical analysis rules (see Okunev and White, 2003). As these considerations are necessarily speculative, it may be reassuring that the reverse chain of argument has some substantiation: if this kind of behaviour were able to generate successful technical trading in the foreign exchange market, it should do so in the equity market. Some studies lend support to this view of equity markets (e.g. Brock, Lakonishok and LeBaron, 1992; Blume, Easley and O'Hara, 1994; Lo, Mamaysky and Wang, 2000; Kavajecz and Odders-White, 2004). It is also interesting to note that "round" figures seem to play a prominent role in stock markets (Donaldson and Kim, 1993). This is, however, clearly an avenue for future foreign exchange market research.

5.4 Technical analysis as providing information about non-fundamental exchange rate determinants

The last position analyzed here—i.e. that technical analysis may provide information about non-fundamental influences on exchange rates—is quite common both in the literature and among market practitioners. For example Taylor and Allen (1992, p.311) mention two recurrent groups of comments made by respondents to their survey of London foreign exchange dealers, namely: "a belief that charts essentially measure swings in market psychology" and "that chart analysis may be largely self-fulfilling". Both views imply that

[37] Popular technical trading rules relying on these specific prices are so-called candlestick formations or stochastics indicators.

exchange rates may not be exclusively dependent on the course of fundamentals but may also react to additional, non-fundamental factors.

This position clearly views the foreign exchange market to a certain degree as inefficient in the sense that prices do not only reflect fundamental information. A prominent model in this vein is DeLong et al. (1990), where not-fully-rational noise traders create risks for rational investors with limited arbitrage capacity. The role of technical analysis in this environment is to provide an instrument to analyze and possibly forecast the behaviour of noise traders. Therefore, technicians are seen as rational agents who exploit noise traders without necessarily bringing exchange rates closer to economic fundamentals.

The notion that there may be social psychological influences on financial markets was noted over twenty years ago by Shiller (1984) and it has been investigated more systematically in later research. Regarding foreign exchange markets, the conceptually similar survey studies of Cheung and Wong (2000), Cheung and Chinn (2001) and Cheung, Chinn and Marsh (2004) directly asked market practitioners about their assessment of the price relevance of several factors that can be linked to psychological influences on the market. The result, presented graphically in Figure 4, clearly shows the importance that foreign exchange dealers attach to psychological forces in the very short run.

Whereas these three survey studies ask for the perceived importance of technical factors in competition with psychological factors, the study by Gehrig and Menkhoff (2006) allows an analysis of the implicit relations between these two factors (the results hold for data from Menkhoff, 1997). In particular, if one relates the weight given by traders to the use of technical analysis and the perceived importance of psychological price influences, a positive correlation becomes obvious (see the lightly shaded bars in Figure 5).

A similar approach can be applied to learn about the possibility of the self-fulfilling nature of technical analysis, which, to date, has not been examined systematically. One reason why this issue has not been examined may be an *ex ante* scepticism against this possibility, as it is well-known that chartists differ markedly in the instruments they use and even more so in their respective calibration (e.g. the precise number of days used in moving average rules), and may also display significant heterogeneity in their forecasts (Allen and Taylor, 1990). Nevertheless, asking those who use technical analysis their opinion as to the self-fulfilling hypothesis leads to a bimodal relation—i.e. there emerge two views: either an “opportunists’ view” whereby chartism is used because it is perceived as self-fulfilling, or a “believers’ view” whereby chartism is seen as an intrinsically valuable methodology rather than merely self-fulfilling in its predictions (see the dark shaded bars in Figure 5). Interestingly, the opportunists' view appears to have gained ground over time (Menkhoff, 1997).[38] Given that the use of technical analysis has also become more widespread over time, this suggests that traders may indeed alter the weight attached to technical analysis in accordance to its perceived forecasting power (as originally suggested by Frankel and Froot, 1986, 1990).

Additional indirect support for non-fundamental price influences in foreign exchange markets is provided by recent models with heterogeneous agents (Hommes, 2005). These models have in common that complex interaction between heterogeneous groups of actors can successfully generate stylised facts in financial markets, such as fat tails in the distribution of returns and volatility clustering. What is remarkable here is the fact that the most prominent way of describing the behaviour of non-fundamentalists is to assume trend-following behaviour, which is often motivated by applying technical analysis (Lux, 1998; Westerhoff, 2003; De Grauwe and Grimaldi, 2006; Reitz and Taylor, 2006).

In a related study modelling the interaction of agents with different horizons, LeBaron (2001) finds that such a computational stock market produces some well-known characteristics of foreign exchange as well. Different time scales of heterogeneous agents are an important subject in foreign exchange (Dacorogna et al., 2001) and seem to be intuitively directly related to the relatively short-term oriented chartists as discussed above (stylised fact 3).

In a recent study using intraday exchange rate data, Dominguez and Panthaki (2006) distinguish three categories of factors generating exchange rate movements: fundamental news, order flow (reflecting private information) and non-fundamental news. The most prominent relation of non-fundamentals news—derived from newswire reports—is to technical analysis. This evidence indicates both that non-fundamental influences may have significant short-run effects on exchange rates and that they may be related to technical analysis.

In another recent innovative study, Schulmeister (2006) analyzes market-wide relations between signals from technical analysis (using 1024 different trading rules), exchange rates and order flow. He finds that during most periods, the trading rules under consideration tend to be on the same side of the market, and so may possibly be pushing exchanges rates by generating similar trading signals. The analysis is then extended to include order flow for a three-month period (the sample period being limited by data availability). During this three-month period the vast majority of the technical analysis considered tended

[38] Of course, the self-fulfilling nature of technical analysis cannot be an example of perpetual motion—returns must ultimately be generated by trading with others. Thus, this view is basically informative about the motivation of users. One may, however, speculate whether users of technical analysis who are motivated solely by the fact that other market participants are using it may in effect end up as market followers often do, i.e. as losers.

to generate trading positions similar to those generated using signals based on order flow. Consequently, this (admittedly short-sample) study suggests that order flow could be the result of technical trading, in addition to the earlier examined sources of information revelation and liquidity trading (Evans and Lyons, 2005a). Thus, Schulmeister conjectures that technical analysis may magnify otherwise small exchange rate changes, contributing to the kind of short-term overreactions mentioned above in a self-fulfilling fashion (see also Farmer and Joshi, 2002).

Although there seems to be some support for the position that technical analysis is an instrument for processing and assimilating information about non-fundamental price determinants, it should be noted that the evidence so far only reveals three facts. First, that a significant proportion of foreign exchange market participants believe in non-fundamental influences on exchange rates. Second, that those who believe more strongly rely more heavily on technical analysis. Third, that participants believing in technical analysis often ascribe its importance to its self-fulfilling nature. These facts would also be consistent with the view that chartists do not understand the fundamental nature of exchange rates. However, there are two further pieces of evidence that give weight to the proposition under review in this sub-section.

First, as discussed above in Sub-Section 5.1, there is no evidence that the use of non-fundamental information—among which technical analysis is perhaps the most important—could be related to indicators of reduced rationality (see Menkhoff, 1998). Second, the position under review here fits well with the puzzle mentioned in the introduction that shorter-term exchange rate movements cannot be explained with existing fundamental models (the so-called “disconnect puzzle”). If there are other forces at work (see e.g. Dominguez and Panthaki, 2006), this would help us solve the puzzle and at the same time provide a rationale for the use of technical analysis.

6 Conclusion

A reading of the literature on the nature and use of technical analysis in the foreign exchange market allows us to draw up a set of stylised facts concerning its nature and use, and also to distinguish a number of arguments that have typically been adduced to explain its continued use.

Indeed, first and foremost among these stylised facts lies the continued and widespread use of technical analysis in the foreign exchange market. Research conducted in most of the major foreign exchange markets during the last decade or so reveals clearly that the use of technical analysis is an important and persistent phenomenon which is highly influential in the decision making of foreign exchange professionals. A similar situation emerges with respect to the profitability of technical analysis. It is beyond question that for major flexible exchange rates and over longer time periods the use of technical analysis may be used to provide excess returns. What is disputed, however, is whether the realization of these profits has to be bought at the cost of taking large risks and whether the profits can fully compensate for this additional risk.

A contribution that we have sought to make in this paper is in relating the available empirical evidence to several positions that have been developed in order to explain the continued use of technical analysis.

The first of these—interpreting the use of technical analysis as an indication of not-fully-rational behaviour—is difficult to reconcile with the fact that virtually all professionals in the market rely on this tool at least to a small degree. Moreover, there is no hard evidence showing that chartists are characterized by temporarily sub-optimal behaviour, or underestimate the risk involved or accept technical analysis as a marketing instrument.

The second position, relating profitability to foreign exchange interventions by the monetary authorities, is a little more satisfying in the sense that it suggests a more solid rationale for the use of technical analysis by rational agents. Also, some stylized facts concerning the profitability of technical analysis—namely that it tends to be more profitable during periods of official intervention—fit well with this position. There is, however, more recent evidence that suggests that it may be large exchange rate movements themselves that may be leading *both* intervention and technical analysis profitability or, equivalently, that the influence of technical analysis, by driving the exchange rate away from the level consistent with the fundamentals, may generate a rationale for official intervention, rather than vice versa, through the coordination channel of intervention effectiveness.

The third position, namely that technical analysis is simply an instrument in the processing and assimilation of market information, can also reconcile the importance of order flows and technical analysis to some degree. The main problem with this position, however, is that it does not explain the reason behind sluggish adjustment to news, preferences for round figures in order placement, etc.

Overall, therefore, perhaps the most satisfying explanation concerning the continued use of technical analysis seems to be position four, whereby technical analysis is seen as an instrument informing traders about non-fundamental price determinants. These forces are more important in the shorter-run, so for a full understanding of exchange rate dynamics, professionals need a combination of several tools, in particular both technical and fundamental analysis. This position also fits well with the stylised fact on the higher profitability of technical analysis in flexible exchange rate markets, as there is some indication that these markets may be characterized by a degree of volatility that is hard to explain by fundamentals alone (Flood and Rose, 1995).

This still leaves open, however, the question of risk-adjusted profitability. If technical analysis has some rationale in the sense of being able to generate profitable trading rules, why does the market process not assimilate or arbitrage these profit opportunities away? The answer may be the same as with fundamental analysis: in well functioning markets one would expect that profit opportunities will be exploited up to an extent where agents feel appropriately compensated for their risk. To take open positions is inherently risky, whether the decision is based on fundamental or technical considerations. In the case of technical analysis, most studies simulate situations where one would need to operate with a horizon of several years and apply some diversification regarding currencies and chartist rules. This is a situation which does not describe a real-world alternative. Thus, this kind of profitability does not contradict the notion of efficient markets, accepting the present limitations of operating horizon (see Shleifer and Vishny, 1997).

What is perhaps most striking from our reading of the literature is that technical analysis remains a passionate obsession of many foreign exchange market professionals. It is clearly an intrinsic part of this market and it has thus to be understood and integrated into economic reasoning at both the macroeconomic and the microstructural levels.

References

Allen, Franklin and Risto Karjalainen. 1999. Using Genetic Algorithms to Find Technical Trading Rules. Journal of Financial Economics, 51, 245-271.

Allen, Helen L. and Mark P. Taylor. 1990. Charts, Noise and Fundamentals in the London Foreign Exchange Market. Economic Journal, 100 (Supplement), 49-59.

____________ and ____________ 1992. Chartist Analysis. in: Peter Newman, Murray Milgate and John Eatwell. (eds.), The New Palgrave Dictionary of Money and Finance, London: MacMillan, 339-342.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold and Clara Vega. 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. American Economic Review, 93, 38-62.

Bank for International Settlements. 2005. Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in April 2004, Basel.

Barberis, Nicholas, Andrei Shleifer and Robert Vishny. 1998. A Model of Investor Sentiment. Journal of Financial Economics, 49, 307-343.

Benartzi, Shlomo and Richard H. Thaler. 1995. Myopic Loss Aversion and the Equity Premium Puzzle. Quarterly Journal of Economics, 110, 75-92.

Bhanumurthy, N. R. 2004. Microstructures in the Indian Foreign Exchange Market. Working Paper, Delhi University.

Blume, Lawrence, David Easley and Maureen O'Hara. 1994. Market Statistics and Technical Analysis – the Role of Volume. Journal of Finance, 49:1, 153-183.

Brock, William A., Josef Lakonishok and Blake LeBaron. 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. Journal of Finance, 47:5, 1731-1764.

Brown, David P. and Robert H. Jennings. 1989. On Technical Analysis. Review of Financial Studies, 2:4, 527-551.

Chaboud, Alan and Blake LeBaron. 2001. Foreign Exchange Market Trading Volume and Federal Reserve Intervention. Journal of Futures Markets, 21, 851-860.

Campbell, John Y., Andrew W. Lo and A. Craig MacKinlay. 1996. The Econometrics of Financial Markets. Princeton: Princeton University Press.

Chang, P.H. Kevin and Carol L. Osler. 1999. Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts. Economic Journal, 109:458, 636-661.

Charlebois, Maxime and Stephen Sapp. 2006. Temporal Patterns in Foreign Exchange Returns and Options. pdf, Richard Ivey School of Business, University of Western Ontario.

Cheung, Yin-Wong and Menzie D. Chinn. 2001. Currency Traders and Exchange Rate Dynamics: A Survey of the US Market. Journal of International Money and Finance, 20, 439-471.

Cheung, Yin-Wong, Menzie D. Chinn and Antonio Garcia Pascual. 2005. Empirical Exchange Rate Models of the Nineties: Are any Fit to Survive?. Journal of International Money and Finance, 24, 1150-1175.

Cheung, Yin-Wong, Menzie D. Chinn and Ian W. Marsh. 2004. How Do UK-based Foreign Exchange Dealers Think their Market Operates?. International Journal of Finance and Economics, 9, 289-306.

Cheung, Yin-Wong and Clement Yuk-Pang Wong. 1999. Foreign Exchange Traders in Hong Kong, Tokyo, and Singapore. in: Theodore Bos and Thomas A. Fetherstone (eds.), Advances in Pacific Basin Financial Markets, Vol.5, Greenwich, Conn.: JAI Press, 111-134.

____________ and ___________ 2000. A Survey of Market Practitioners' Views on Exchange Rate Dynamics. Journal of International Economics, 51, 401-423.

Clarida, Richard H. and Mark P. Taylor. 1997. The Term Structure of Forward Exchange Premiums and the Forecastability of Spot Exchange Rates: Correcting the Errors. Review of Economics and Statistics, 79, 353-361.

Clarida, Richard H., Lucio Sarno, Mark P. Taylor and Giorgio Valente. 2003. The Out-of-Sample Success of Term Structure Models as Exchange Rate Predictors: A Step Beyond. Journal of International Economics, 60, 61-83.

Clyde, William C. and Carol L. Osler. 1997. Charting: Chaos Theory in Disguise?. Journal of Futures Markets, 17:5, 489-514.

Cochrane, John H. 2005. Asset Pricing. Revised Edition, Princeton: Princeton University Press.

Cornell, W. Bradford and J. Kimball Dietrich. 1978. The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates. Review of Economics and Statistics, 60:1, 111-120.

Cornell, W. Bradford and Richard Roll. 1981. Strategies for Pairwise Competitions in Markets and Organizations. Bell Journal of Economics, 12:1, 210-213.

Curcio, Riccardo and Charles Goodhart. 1992. When Support/Resistence Levels Are Broken, Can Profits Be Made? Evidence from the Foreign Exchange Market. London School of Economics Financial Markets Group, Discussion Paper, No.142.

____________ and ____________ 1993. Chartism: A Controlled Experiment. Journal of International Securities Markets, 7, 173-186.

Curcio, Riccardo, Charles Goodhart, Dominique Guillaume and Richard Payne. 1997. Do Technical Trading Rules Generate Profits? Conclusions from the Intra-Day Foreign Exchange Market. International Journal of Finance and Economics, 2:4, 267-280.

Dacorogna, Michael M., Ramazan Gencay, Ulrich A. Mueller, Richard B. Olsen and Olivier V. Pictet. 2001. An Introduction to High-Frequency Finance. San Diego, CA: Academic Press.

De Grauwe, Paul and Danny Decupere. 1992. Psychological Barriers in the Foreign Exchange Market. Journal of International and Comparative Economics, 1:2, 87-101.

De Grauwe, Paul and Marianna Grimaldi. 2006. The Exchange Rate in a Behavioural Framework. Princeton: Princeton University Press, forthcoming.

____________ and ______________ 2006a. Exchange Rate Puzzles: A Tale of Switching Attractors. European Economic Review, 50, 1-33.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers and Robert J. Waldmann. 1990. Noise Trader Risk in Financial Markets. Journal of Political Economy, 98:4, 703-738.

Dewachter, Hans. 1997. Sign Predictions of Exchange Rate Changes: Charts as Proxies for Bayesian Inferences. Review of World Economics, 133:1, 39-55.

____________ 2001. Can Markov Switching Models Replicate Chartist Profits in the Foreign Exchange Market?. Journal of International Money and Finance, 20, 25-41.

Dewachter, Hans and Marco Lyrio. 2005. The Economic Value of Technical Trading Rules: A Nonparametric Utility-Based Approach. International Journal of Finance and Economics, 10, 41-62.

Dominguez, Kathryn M.E. 2003. The Market Microstructure of Central Bank Intervention. Journal of International Economics, 59, 25-45.

Dominguez, Kathryn M.E. and Freyan Panthaki. 2006. What Defines "News" in Foreign Exchange Markets?. Journal of International Money and Finance, 25, 168-198.

Donaldson, R. Glen and Harold Y. Kim. 1993. Price Barriers in the Dow Jones Industrial Average. Journal of Financial and Quantitative Analysis, 28:3, 313-330.

Dooley, Michael P. and Jeffrey R. Shafer. 1976. Analysis of Short-Run Exchange Rate Behaviour: March 1973 to September 1975. Federal Reserve Board, International Finance Discussion Paper, No. 123.

____________ and ____________ 1983. Analysis of Short-Run Exchange Rate Behaviour: March 1973 to November 1981. in: David Bigman und Teito Taya (eds.), Exchange Rate and Trade Instability, Cambridge, Mass.: Ballinger, 43-69.

Dueker, Michael and Christopher J. Neely. 2005. Can Markov Switching Models Predict Excess Foreign Exchange Returns?. Journal of Banking and Finance, forthcoming.

Easley, David, Maureen O'Hara and P. S. Srinivas. 1998. Option Volume and Stock Prices: Evidence on where Informed Traders Trade. Journal of Finance, 53, 431-465.

Engel, Charles and James D. Hamilton. 1990. Long Swings in the Dollar: Are They in the Data and Do Markets Know It?. American Economic Review, 80, 689-713.

Evans, Martin D.D. and Richard K. Lyons. 2002. Order Flow and Exchange Rate Dynamics. Journal of Political Economy, 110, 170-180.

____________ and ____________ 2005a. Do Currency Markets Absorb News Quickly? Journal of International Money and Finance, 24, 197-217.

____________ and ____________ 2005b. Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting. American Economic Review, 95, 405-414.

Fama, Eugene F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25:2, 383-417.

____________ 1998. Market Efficiency, Long-term Returns, and Behavioral Finance. Journal of Financial Economics, 49, 283-306.

Fama, Eugene F. and Kenneth R. French. 1996. Multifactor Explanations of Asset Pricing Anomalies. Journal of Finance, 51:1, 55-84.

Farmer, J. Doyne and Shareen Joshi. 2002. The Price Dynamics of Common Trading Strategies. Journal of Economic Behavior and Organization, 49, 149-171.

Fiess, Norbert and Ronald MacDonald. 1999. Technical Analysis in the Foreign Exchange Market: A Cointegration-Based Approach. Multinational Finance Journal, 3:3, 147-172.

____________ and ____________ 2002. Towards the Fundamentals of Technical Analysis: Analysing the Information Content of High, Low and Close Prices. Economic Modelling, 19:3, 353-374.

Flood, Robert P. and Andrew K. Rose. 1995. Fixing Exchange Rates: A Virtual Quest for Fundamentals. Journal of Monetary Economics, 36, 3-37.

Frankel, Jeffrey A. and Kenneth A. Froot. 1986. Understanding the U.S. Dollar in the Eighties: The Expectations of Fundamentalists and Chartists. Economic Record, 62, 24-38.

____________ and ____________ 1990. Chartists, Fundamentalists, and Trading in the Foreign Exchange Market. American Economic Review, 80:2, 181-185.

____________ and ____________ 1990a. Chartists, Fundamentalists and the Demand for Dollars. in: Anthony S. Courakis and Mark P. Taylor (eds.), Private Behaviour and Government Policy in Interdependent Economies, Oxford: Clarendon Press, 73-126.

Frankel, Jeffrey A. and Andrew Rose. 1995. Empirical Research on Nominal Exchange Rates. in: Gene Grossmann and Kenneth Rogoff (eds.), Handbook of International Economics, Vol. III, Amsterdam et al: North-Holland, 1689-1729.

Frenkel, Michael and Georg Stadtmann. 2004. Trading Rule Profitability and Central Bank Interventions in the Dollar-Deutschmark Market. Jahrbuecher fuer Nationaloekonomie und Statistik, 224:6, 653-672.

Froot, Kenneth A. and Takatoshi Ito. 1989. On the Consistency of Short-run and Long-run Exchange Rate Expectations. Journal of International Money and Finance, 8, 487-510.

Gehrig, Thomas and Lukas Menkhoff. 2004. The Use of Flow Analysis in Foreign Exchange: Exploratory Evidence. Journal of International Money and Finance, 23, 573-594.

____________ and ____________ 2006. Extended Evidence on the Use of Technical Analysis in Foreign Exchange. International Journal of Finance and Economics, forthcoming.

Gencay, Ramazan. 1999. Linear, Non-Linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules. Journal of International Economics, 47, 91-107.

Gencay, Ramazan, Michael Dacorogna, Richard Olson and Olivier Pictet. 2003. Foreign Exchange Trading Models and Market Behavior. Journal of Economic Dynamics and Control, 27:6, 909-935.

Gigerenzer, Gerd and Peter M. Todd. 1999.Fast and Frugal Heuristics: The Adaptive Toolbox. in: Gerd Gigerenzer, Peter M. Todd and the ABC Research Group (eds.), Simple Heuristics that Make Us Smart. Oxford et al.: Oxford University Press, 3-37.

Goodhart, Charles A.E. 1988. The Foreign Exchange Market: A Random Walk with a Dragging Anchor. Economica, 55:220, 437-460.

Goodman, Stephen H. 1979. Foreign Exchange Rate Forecasting Techniques: Implications for Business and Policy. Journal of Finance, 34:2, 415-427.

Griffin, John M., Jeffrey H. Harris and Selim Topaloglu. 2003. The Dynamics of Institutional and Individual Trading. Journal of Finance, 58, 2285-2320.

Grinblatt, Mark, Sheridan Titman and Russ Wermers. 1995. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. American Economic Review, 85, 1088-1105.

Grinold, Richard C., and Ronald N. Kahn. 2000. Active Portfolio Management (second edition). New York: McGraw-Hill.

Grossman, Sanford and Joseph E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. American Economic Review, 70, 393-408.

Group of Thirty. 1985. The Foreign Exchange Market in the 1980s. New York.

Hellwig, Martin F. 1982. Rational Expectations Equilibrium with Conditioning on Past Prices: A Mean-Variance Example. Journal of Economic Theory, 26, 279-312.

Henderson, Callum. 2002. Currency Strategy: The Practitioner's Guide to Currency Investing, Hedging and Forecasting. Chichester: John Wiley and Sons.

Hommes, Cars. 2005. Heterogeneous Agent Models in Economics and Finance. Tinbergen Institute Discussion Paper 056.

Hsu, Po-Hsuan and Chung-Ming Kuan. 2005. Reexamining the Profitability of Technical Analysis with Data Snooping Checks. Journal of Financial Econometrics, 3:4, 606-628.

Ito, Takatoshi. 1990. Foreign Exchange Rate Expectations: Micro Survey Data. American Economic Review, 80:3, 434-449.

Ito, Takatoshi, Richard Lyons and Michael T. Melvin. 1998. Is there Private Information in the FX Market? The Tokyo Experiment. Journal of Finance, 53, 1111-1130.

Jegadeesh, Narasimhan and Sheridan Titman. 2001. Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. Journal of Finance, 56, 699-720.

Kavajecz, Kenneth A. and Elizabeth R. Odders-White. 2004. Technical Analysis and Liquidity Provision. Review of Financial Studies, 17:4, 1043-1071.

Kho, Bong-Chan. 1996. Time-Varying Risk-Premia, Volatility, and Technical Trading Rule Profits: Evidence from Foreign Currency Futures Markets. Journal of Financial Economics, 41, 249-290.

Kilian, Lutz and Mark P. Taylor. 2003. Why Is It so Difficult to Beat the Random Walk Forecast of Foreign Exchange Rates? Journal of International Economics, 60, 85-107.

Kozhan, Roman and Mark Salmon. 2006. On the Predictability of Tick by Tick Exchange Rates Using the Structure of the Order Book. Discussion Paper, Warwick Business School.

LeBaron, Blake. 1999. Technical Trading Rule Profitability and Foreign Exchange Intervention. Journal of International Economics, 49, 125-143.

____________ 2000. Technical Trading Profitability in Foreign Exchange Markets in the 1990s. Working Paper, Brandeis University.

____________ 2001. Empirical Regularities from Interacting Long- and Short-Memory Investors in an Agent-Based Stock Market. IEEE Transactions on Evolutionary Computation, 5:5, 442-455.

Lee, Chun I. and Ike Mathur. 1996. Trading Rule Profits in European Currency Spot Cross-Rates. Journal of Banking and Finance, 20:5, 949-962.

Levich, Richard M. 1985. Empirical Studies of Exchange Rates: Price Behaviour, Rate Determination and Market Efficiency. in: Ronald W. Jones and Peter B. Kenen (eds.), Handbook of International Economics, Vol.II, Amsterdam et al.: North-Holland, 979-1040.

Levich, Richard M. and Lee R. Thomas. 1993. The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach. Journal of International Money and Finance, 12:5, 451-474.

Lewellen, Jonathan, Stefan Nagel and Jay Shanken. 2006. A Skeptical Appraisal of Asset-Pricing Tests. NBER Working Paper 12360.

Lewis, Karen K. 1999. Trying to Explain Home Bias in Equities and Consumption. Journal of Economic Literature, 37, 571-608.

Lillo, Fabrizio and J. Doyne Farmer. 2004. The Long Memory of the Efficient Market. Studies in Nonlinear Dynamics and Econometrics, 8:3.

Lo, Andrew W., Harry Mamaysky and Jiang Wang. 2000. Foundations of Technical Analysis. Journal of Finance, 55:4, 1705-1765.

Logue, Dennis E. and Richard J. Sweeney. 1977. White Noise in Imperfect Markets: The Case of the Franc/Dollar Exchange Rate. Journal of Finance, 32, 761-768.

Logue, Dennis E., Richard J. Sweeney and Thomas D. Willett. 1978. Speculative Behaviour of Foreign Exchange Rates during the Current Float. Journal of Business Research, 6, 159-174.

Lothian, James and Mark P. Taylor. 1996. Real Exchange Rate Behaviour: The Recent Float from the Perspective of the Past Two Centuries. Journal of Political Economy, 104, 488-509.

Lucke, Bernd. 2003. Are Technical Trading Rules Profitable? Evidence for Head-and-Shoulder Rules. Applied Economics, 35:1, 33-40.

Lui, Yu-Hon and David Mole. 1998. The Use of Fundamental and Technical Analysis by Foreign Exchange Dealers: Hong Kong Evidence. Journal of International Money and Finance, 17, 535-545.

Lux, Thomas. 1998. The Socio-Economic Dynamics of Speculative Markets: Interacting Agents, Chaos, and Fat Tails of Return Distributions. Journal of Economic Behavior and Organization, 33, 143-165.

Lyons, Richard K. 2001. The Microstructure Approach to Exchange Rates. Cambridge: MIT Press.

Malkiel, Burton G. 1996. A Random Walk down Wallstreet. New York: W.W. Norton, 6. ed.

Mark, Nelson. 1995. Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability. American Economic Review, 85, 201-218.

Marsh, Ian W. 2000. High-frequency Markov Switching Models in the Foreign Exchange Market. Journal of Forecasting, 19, 123-134.

Melvin, Michael, Michael J. Sager and Mark P. Taylor. 2006. Bank of England Interest Rate Announcements and the Foreign Exchange Market. Discussion Paper, Centre for Economic Policy Research.

Menkhoff, Lukas. 1997. Examining the Use of Technical Currency Analysis. International Journal of Finance and Economics, 2:4, 307-318.

____________ 1998. The Noise Trading Approach – Questionnaire Evidence from Foreign Exchange. Journal of International Money and Finance, 17, 547-564.

Menkhoff, Lukas and Manfred Schlumberger. 1995. Persistent Profitability of Technical Analysis on Foreign Exchange Markets?. Banca Nazionale del Lavoro Quarterly Review, 48, 189-216.

Neely, Christopher J. 1997. Technical Analysis in the Foreign Exchange Market: A Layman's Guide. Federal Reserve Bank of St. Louis Review, 79:5, 23-38.

____________ 1998. Technical Analysis and the Profitability of U.S. Foreign Exchange Intervention. Federal Reserve Bank of St. Louis Review, 80:4, 3-17.

____________ 2002. The Temporal Pattern of Trading Rule Returns and Exchange Rate Intervention: Intervention Does not Generate Technical Trading Profits. Journal of International Economics, 58, 211-232.

Neely, Christopher J. and Paul A. Weller. 1999. Technical Trading Rules in the European Monetary System. Journal of International Money and Finance, 18, 429-458.

____________ and ____________ 2001. Technical Analysis and Central Bank Intervention. Journal of International Money and Finance, 20:7, 949-970.

____________ and ____________ 2003. Intraday Technical Trading in the Foreign Exchange Market. Journal of International Money and Finance, 22, 223-237.

Neely, Christopher J., Paul A. Weller and Robert Dittmar. 1997. Is Technical Analysis Profitable in the Foreign Exchange Market? A Genetic Programming Approach. Journal of Financial and Quantitative Analysis, 32, 405-436.

Neely, Christopher J., Paul A. Weller and Joshua M. Ulrich. 2006. The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market. pdf, Research Department, Federal Reserve Bank of St Louis.

Oberlechner, Thomas. 2001. Importance of Technical and Fundamental Analysis in the European Foreign Exchange Market. International Journal of Finance and Economics, 6:1, 81-93.

____________ 2004. The Psychology of Foreign Exchange Markets. Wiley.

Oberlechner, Thomas and Carol L. Osler. 2006. Overconfidence in Currency Markets. Discussion Paper, Brandeis University.

Okunev, John and Derek White. 2003. Do Momentum-Based Strategies Still Work in Foreign Currency Markets?. Journal of Financial and Quantitative Analysis, 38:2, 425-447.

Olson, Dennis. 2004. Have Trading Rule Profits in the Currency Markets Declined over Time?. Journal of Banking and Finance, 28, 85-105.

Osler, Carol L. 2000. Support for Resistance: Technical Analysis and Intraday Exchange Rates. Federal Reserve Bank of New York Economic Policy Review, 6:2, 53-68.

____________ 2003. Currency Orders and Exchange-Rate Dynamics: Explaining the Success of Technical Analysis. Journal of Finance, 58, 1791-1819.

____________ 2005. Stop-Loss Orders and Price Cascades in Currency Markets. Journal of International Money and Finance, 24, 219-242.

Park, Cheol-Ho and Scott H. Irwin. 2004. The Profitability of Technical Analysis: A Review. Working Paper, University of Illinois at Urbana-Champaign.

____________ and ____________ 2005. A Reality Check on Technical Trading Rule Profits in US Futures Markets. Working Paper, University of Illinois at Urbana-Champaign.

Peiers, Bettina. 1997. Informed Traders, Intervention, and Price Leadership: A Deeper View of the Microstructure of the Foreign Exchange Market. Journal of Finance, 52, 1589-1614.

Pilbeam, Keith. 1995. The Profitability of Trading in the Foreign Exchange Market: Chartists, Fundamentalists, and Simpletons. Oxford Economic Papers, 47:3, 437-452.

Poole, William. 1967. Speculative Prices as Random Walks: An Analysis of Ten Time Series of Flexible Exchange Rates. Southern Economic Journal, 33, 468-478.

____________ 1967a. The Stability of the Canadian Flexible Exchange Rate, 1950 -1962. Canadian Journal of Economics, 33:2, 205-217.

Qi, Min and Yangru Wu. 2006. Technical Trading-Rule Profitability, Data Snooping, and Reality Check: Evidence from the Foreign Exchange Market. Journal of Money, Credit and Banking, forthcoming.

Reitz, Stefan and Mark P. Taylor. 2006. The Coordination Channel of Foreign Exchange Intervention: A Nonlinear Microstructural Analysis. Discussion Paper, Deutsche Bundesbank.

Saacke, Peter. 2002. Technical Analysis and the Effectiveness of Central Bank Intervention. Journal of International Money and Finance, 21:4, 459-479.

Sager, Michael J. and Mark P. Taylor. 2004. The Impact of European Central Bank Governing Council Announcements on the Foreign Exchange Market: A Microstructural Analysis. Journal of International Money and Finance, 23, 1043-51.

Sager, Michael J. and Mark P. Taylor. 2006. Under the Microscope: The Structure of the Foreign Exchange Market. International Journal of Finance and Economics, 11(1), 81-95.

Sapp, Stephen. 2002. Price Leadership in Foreign Exchange Markets. Journal of Financial and Quantitative Analysis, 37, 425-448.

____________ 2004. Are all Central Bank Interventions Created Equal? An Empirical Investigation. Journal of Banking and Finance, 28, 443-474.

Sarno, Lucio and Mark P. Taylor. 2001. The Microstructure of the Foreign Exchange Market: A Selective Survey of the Literature. Princeton Studies in International Economics, 89, International Economics Section, Princeton University.

____________ and ____________ 2001a. Official Intervention in the Foreign Exchange Market: Is It Effective and, If So, How Does It Work? Journal of Economic Literature, 39:3, 839-868.

____________ and ____________ 2002. The Economics of Exchange Rates. Cambridge and New York: Cambridge University Press.

Schulmeister, Stephan. 1987. An Essay on Exchange Rate Dynamics. WZB Discussion Paper IIM/LMP 87-8 (Wissenschaftszentrum), Berlin.

____________ 2005. Components of the Profitability of Technical Currency Trading. Discussion Paper, Austrian Institute of Economic Research.

____________ 2006. The Interaction between Technical Currency Trading and Exchange Rate Fluctuations. Finance Research Letters, 3:3, 212-233.

Schwert, G. William. 2002. Anomalies and Market Efficiency. NBER Working Paper 9277.

Sharpe, William F. 1966. Mutual Fund Performance. Journal of Business, 39:1, 119-138.

Shiller, Robert J. 1984. Stock Prices and Social Dynamics. Brookings Papers on Economic Activity, No.2, 457-498.

Shleifer, Andrei and Robert W. Vishny. 1997. The Limits of Arbitrage. Journal of Finance, 52, 35-55.

Silber, William L. 1994. Technical Trading: When it Works and When it Doesn't. Journal of Derivatives, 1:3, 39-44.

Snyder, Mark. 2005. Chair's Letter, in Foreign Exchange Committee 2005 Annual Report. Federal Reserve Bank of New York.

Surajas, Patchara and Richard J. Sweeney. 1992. Profit-Making Speculation in Foreign Exchange Markets. Boulder: Westview Press.

Sweeney, Richard J. 1986. Beating the Foreign Exchange Market. Journal of Finance, 41:1, 163-182.

____________ 1997. Do Central Banks Lose on Foreign-Exchange Intervention? A Review Article. Journal of Banking and Finance, 21:11, 1667-1684.

Sylla, Richard. 1992. Chartists' Language. in: Peter Newman et al. (eds.), The New Palgrave Dictionary of Money and Finance, London: MacMillan, 342-344.

Szakmary, Andrew C. and Ike Mathur. 1997. Central Bank Intervention and Trading Rule Profits in Foreign Exchange Markets. Journal of International Money and Finance, 16:6, 513-535.

Taylor, Alan M. and Mark P. Taylor. 2004. The Purchasing Power Parity Debate. Journal of Economic Perspectives, 18:4, 135-158.

Taylor, Mark P. 1994. Exchange Rate Behavior Under Alternative Exchange Rate Regimes'. in: Peter Kenen (ed.), Understanding Interdependence: The Macroeconomics of the Open Economy, Princeton: Princeton University Press, 34-83.

____________ 1995. The Economics of Exchange Rates. Journal of Economic Literature, 33, 13-47.

____________ 2004. Is Official Exchange Rate Intervention Effective?. Economica. 71, 1–11.

Taylor, Mark P. and Helen Allen. 1992. The Use of Technical Analysis in the Foreign Exchange Market. Journal of International Money and Finance, 11, 304-314.

Taylor, Stephen J. 1992. Rewards Available to Currency Futures Speculators: Compensation for Risk or Evidence of Inefficient Pricing?. Economic Record, 68, 105-116.

Treynor, Jack L. and Robert Ferguson. 1985. In Defense of Technical Analysis. Journal of Finance, 40:3, 757-775.

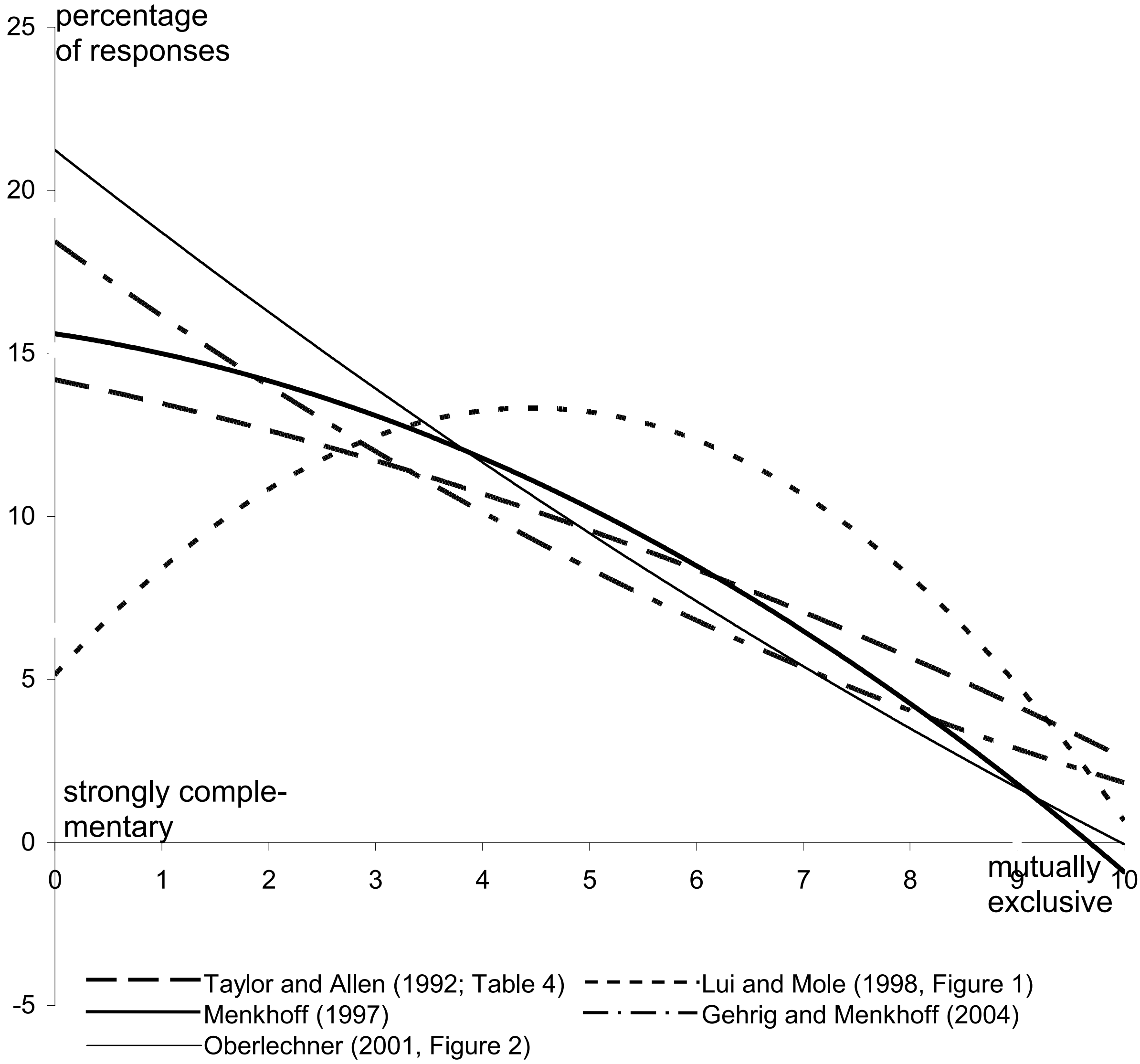
Vigfusson, Robert. 1997. Switching between Chartists and Fundamentalists: A Markov Regime-Switching Approach. International Journal of Finance and Economics, 2, 291-305.

Westerhoff, Frank H. 2003. Expectations Driven Distortions in the Foreign Exchange Market. Journal of Economic Behavior and Organization, 51, 389-412.

White, Halbert. 2000. A Reality Check for Data Snooping. Econometrica, 68:5, 1097-1126.

Wilder, J. W. Jr. 1978. New Concepts in Technical Trading Systems. Greensboro, NC: Hunter Publishing Company.

Figure 1. On the perceived complementarity of technical and fundamental analysis



Note: The regressions are calculated as best fit of a polynomial of second order.

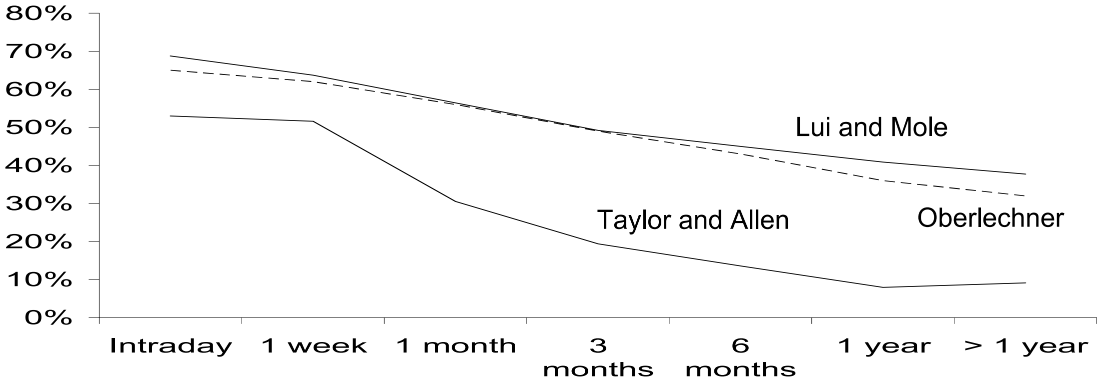
The data from Menkhoff and Gehrig and Menkhoff are transformed in the following way: the individual weight given to fundamental analysis (f) and to technical analysis (t) is put into one measure x. x = | f - t | : (f + t) * 100. The percentage is then put into the scale 0 to 10 according to: x < 10% → 0; 10% ≤ x < 20% → 1; ...; 90% ≤ x < 100% → 9; 100% → 10

The data from Oberlechner are transformed as follows: < 6 (strong complementarity) → 0, < 5 → 2, < 4 and < 7 → 4, < 3 and < 8 → 6, < 2 and < 9 → 8, < 1 and < 10 → 10 (each value multiplied by 0.6 to account for different scaling).

Figure 2. The relative importance of technical analysis depending on the horizon of decision-making

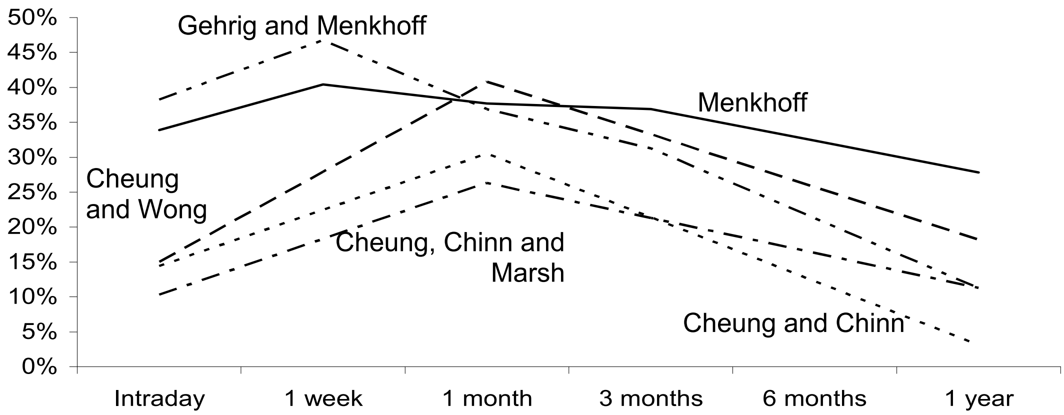
A. Studies considering technical and fundamental analysis only

relative weight of technical analysis



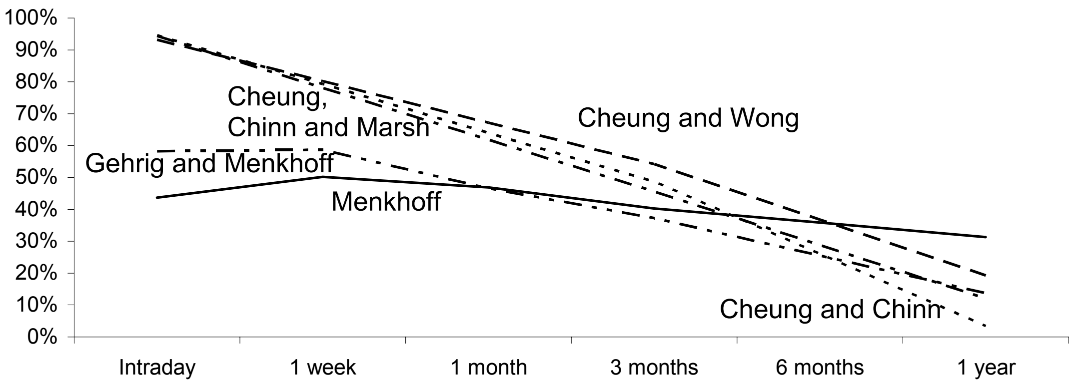
B. Studies considering also further influences

relative weight of technical analysis



C. Studies in B, here without further influences, i.e. relating only the weight of technical and fundamental analysis to each other

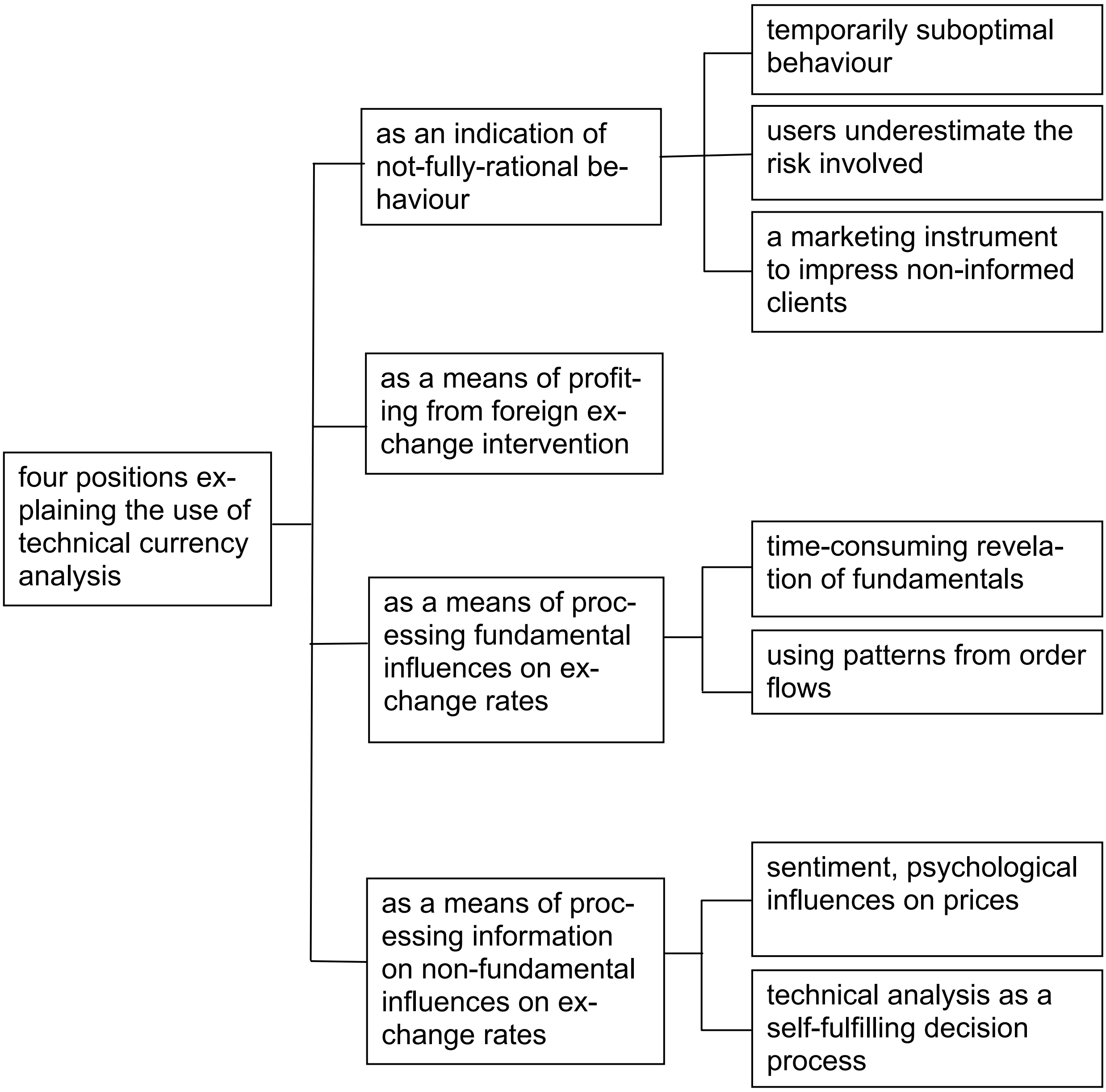
relative weight of technical analysis



Notes: The relative weight of technical analysis is calculated as the weight of technical analysis to the sum of technical plus fundamental analysis. Horizons are taken from Taylor and Allen (1992), Lui and Mole (1998); importance (scale 0-10) in Oberlechner (2001); Figure 1 is transformed into percentage points; Menkhoff (1998) and Gehrig and Menkhoff (2004) are transformed: "few days" into "1 week", "few weeks" into "1 month", "2 to 6 months" into "3 months" and "6 to 12 months" into "1 year", data for "6 months" is interpolated; Cheung and Wong (2000), Cheung and Chinn (2001) and Cheung, Chinn and Marsh (2004) are transformed: "medium run" (<6 months) into "1 month" and "long run" (>6 months) into "1 year", data for "1 week" , "3 months" and "6 months" are interpolated.

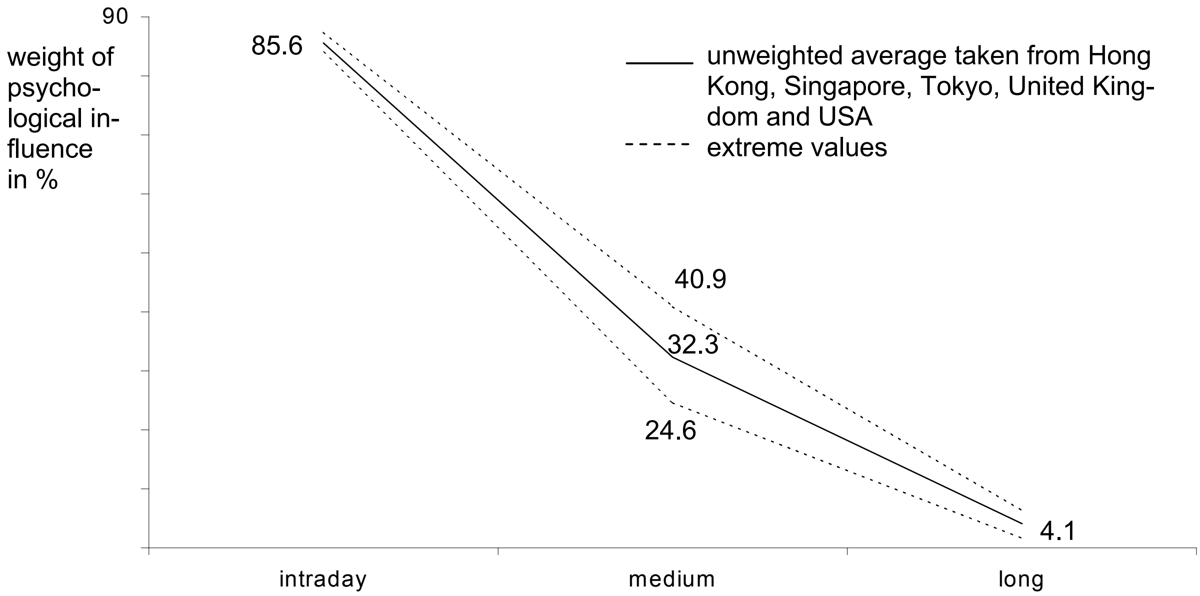
MT-F2

Figure 3. An overview of explanations for the use of technical analysis on foreign exchange markets



,

Figure 4. The perceived importance of psychological influences on exchange rate determination

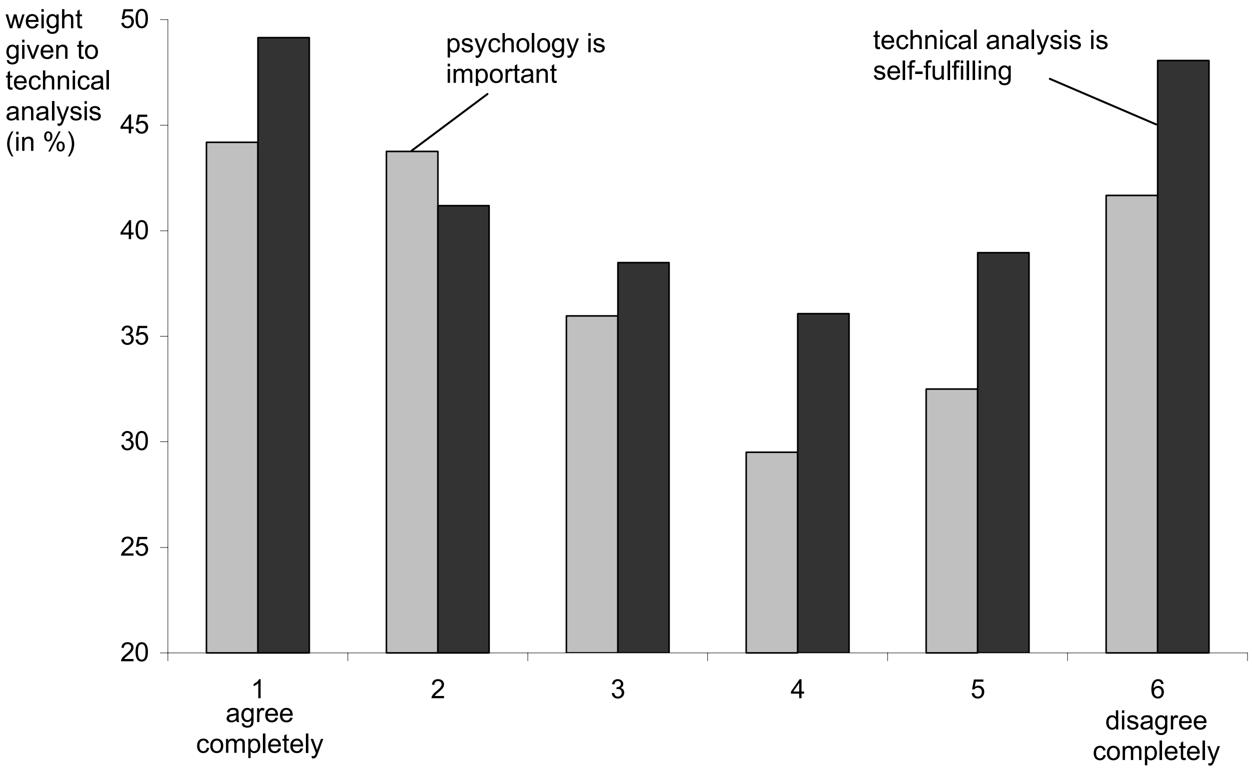


Notes: Data are taken from Cheung and Wong (2000, Table 4.c), Cheung and Chinn (2001, Figure 8.c) and Cheung, Chinn and Marsh (2004, p. 305). Psychological influences is defined as the sum of "bandwagon effects", "over-reaction to news" and "speculative forces".

Figure 5. The weight given to technical analysis in relation to a psychological rationale for its use and the ‘self-fulfilling’ rationale for its use

Question: "How much importance do fundamentals and psychology have for exchange rate movements?"
() People are not machines; thus psychology is clearly more important than fundamentals.

Question: "What is in your opinion the value of technical analysis?"
() I regard technical analysis only because others regard it.



Coefficient of rank correlation of higher weight given to technical analysis with

- “Psychology is important”: -0.220** (P=0.002), n=200
- “Technical analysis is self-fulfilling”: -0.069 (P=0.334), n=197

Notes: Data are taken from the study Gehrig and Menkhoff (2006). Please note that the y-axis starts at 20%.

Table 1. Information on questionaire survey studies

Study	time of survey	financial center	target group	number of responses	response rate
Taylor and Allen (1992)	1988	London	chief FX dealers	213	60.3%
Menkhoff (1997)	1992	Germany	FX dealers; int'l fund managers	205	41.3%
Lui and Mole (1998)	1995	Hong Kong	FX dealers	153	18.8%
Cheung and Wong (2000)	1995/96	Hong Kong, Singapore, Tokyo	FX dealers	392	20.0%
Oberlechner (2001)	1996	Switzerland, United Kingdom, (Austria, Germany)	FX dealers; (financial journalists)	321 (59)	53.5% (29.5%)
Cheung and Chinn (2001)	1996/97	United States	FX dealers	142	8.1%
Cheung, Chinn and Marsh (2004)	1998	United Kingdom	FX dealers	110	5.8%
Gehrig und Menkhoff (2004)	2001	Germany, (Austria)	FX dealers; int'l fund managers	203	51.9%

Table 2. The importance of technical analysis according to questionnaire surveys

Study	form of analysis for decision making	some use of technical analysis	share of technical plus fundamental analysis to total forms[(2)]	share of technical analysis to technical plus fundamental analysis[(2)]	the relation between the weight of technical analysis and horizon
Taylor and Allen (1992)	fundamental analysis; technical analysis	89.4%	100%	32%[(4)]	strictly negative
Menkhoff (1997)	fundamental; technical; flow analysis	>90%	82%	45%	weakly hump-shaped
Lui and Mole (1998)	fundamental; technical	~100%	100%	51%[(5)]	strictly negative
Cheung and Wong (2000)[(1)]	fundamental; technical; bandwagon; overreaction; speculative forces	n.a.	62%[(3)]	40%[(3)]	strongly hump-shaped
Oberlechner (2001)	fundamental; technical	>98%	100%	49%	strictly negative
Cheung and Chinn (2001)[(1)]	see Cheung and Wong (2000)	n.a.	56%	29%	strongly hump-shaped
Cheung, Chinn and Marsh (2004)	see Cheung and Wong (2000)	n.a.	49%[(6)] 54%[(7)]	47%[(6)] 29%[(7)]	strongly hump-shaped
Gehrig and Menkhoff (2004)	fundamental; technical; flows analysis	> 90%	77%	53%	weakly hump-shaped

Notes: (1) These studies do not directly ask for analytical tools but for "factors determining exchange rate movements".
(2) Unweighed averages of values for different horizons.
(3) Data based on Hong Kong only (values for Singapore and Tokyo are similar).
(4) Share is calculated as ratio of scale values 0 to 4 / scale values 0 to 4 plus 6 to 10 (i.e. preference for technical analysis to total preferences); weighed with share of respondents at respective horizon (see Taylor and Allen, 1992, Table 3 B first column).
(5) Share is calculated as ratio of importance given to technical analysis to total.
(6) Traders were asked to select the technique which best characterizes their dealing method.
(7) This value is a more indirect indication and is derived from the same question as mentioned in footnote (1).

Table 3. The importance of technical analysis in several sub-groups and at typical forecasting horizons

Question: "Please evaluate the importance of the three following information types for your typical decision making, by distributing a total of 100 points. For information types which you do not use, please give 0 points."
... Fundamentals (economic, political)
... Technical Analysis (charts, quantitative methods)
... Flows (who is doing what, which customer orders are existing)

	Menkhoff (1997, 1998)				Gehrig and Menkhoff (2006)		
Horizon	chief FX dealers	core FX dealers	other FX dealers	int'l fund managers	chief FX dealers	other FX dealers	int'l fund managers
Intraday	30.5	36.6	23.2	n.a.	45.0	37.3	n.a.
Few days	37.8	38.6	44.0	45.0	45.9	45.1	52.5
Few weeks	34.3	42.5	40.6	35.9	46.9	37.3	32.8
2 to 6 months	42.6	50.0	29.3	36.1	28.3	31.7	31.7
6 to 12 months	(20)	n.a.	(20)	30.0	(0)	n.a.	(15.0)
> 12 months	n.a.	n.a.	(40)	n.a.	(100)	(30)	n.a.
Mean	35.4	38.4	39.9	36.1	44.9	40.0	37.0
n	44	66	39	50	42	102	58

Notes: Data are from the studies Menkhoff (1997, 1998) and Gehrig and Menkhoff (2006). The first value of 30.5 says that chief FX dealers who have a typical intraday forecasting horizon give technical analysis a weight of 30.5% (out of 100% for fundamental, technical and order flow analysis). Shaded cells mark the typical horizon (median value) for decision making of the respective group (e.g. 49% of core FX dealers mark intraday as their typical horizon). Numbers in parenthesis refer to groups with 1 to 3 responses.

Table 4. Earlier studies examining the profitability of technical analysis in foreign exchange markets

Study	period covered	number of exchange rates	form of technical analysis	consideration of trans-action costs	consideration of interest rates	consideration of risk	excess returns of technical analysis
Poole (1967)	1919-24/29	9	10 filters	no	No	no	+
Poole (1967a)	1950-62	1	12 filters	no	No	no	+
Dooley and Shafer (1976)	1973-75	8	filter				+
Logue and Sweeney (1977)	1970-74	1	14 filters	yes	no	no	+
Logue, Sweeney and Willett (1978)	1973-76	7	11 filters	no	no	no	+
Cornell and Dietrich (1978)	1973-75	6	13 filters, 27 mov. averages	yes	no	yes	+
Dooley and Shafer (1983)	1973-81	9	7 filters	yes	yes	no	+
Sweeney (1986)	1973-80	10	7 filters	yes	partially	yes	+
Schulmeister (1987)	1973-86	1	9 filters, 9 mov. av., 5 momentum, 1 point & figure	yes	partially	no	+

Table 5. Suggested risk adjustments in assessing technical analysis' excess returns

Study	period covered	number of cases(1)	standard of comparison	risk adjustment	risk-adjusted excess returns
Cornell and Dietrich (1978)(2)	1973-75	6	S&P 500	beta of currency with S&P 500	+
Sweeney (1986)	1973-80	70	B&H (buy and hold)	constant risk premium equivalent to uncovered interest parity-notation	+
Taylor (1992)	1981-87	16	S&P 500 B&H	beta with S&P 500; time-varying risk premia estimated on AR(1) premia processes and the UIP	+ +
Menkhoff and Schlumberger (1995)	1981-91	129	B&H	Sharpe ratio; risk-return-ratio of monthly return differences against B&H	+ -
Kho (1996)	1980-91	72	MSCI (in excess of one week $ interest rates)	covariation of currency returns with world market portfolio excess returns	-
Chang and Osler (1999)	1973-94	24	S&P 500, Nikkei, DAX	Sharpe ratio with S&P 500; beta with national index	+ +
Neely (1997)	1974-97	40	S&P 500	Sharpe ratio; beta with S&P 500	+ +

Notes: (1) Cases are the product of currencies times rules times models (if applicable).
(2) Incomplete documentation of results; favorable outcomes refer to ex post selection of best technical analysis rules.

Table 6. The use of technical analysis as a sign of temporarily suboptimal behaviour

Hypothesis being tested	aggregated figures for chartists v. others	Pearson χ^2	probability
1. Chartists have the same age as other market participants.	younger than 35 years: chartists 55.56% v. others 49.61%	0.645	(0.419)
2. Chartists reach senior positions as often as other market participants.	senior positions reached: chartists 31.94% v. others 24.22%	1.395	(0.237)
3. Chartists have achieved the same level of education as other market participants.	university level achieved: chartists 24.64% v. others 32.28%	1.254	(0.263)

Notes: The source is Gehrig and Menkhoff (2006), Chartists are defined as respondents who attach a greater weight to technical analysis than to either fundamental or flow information. The number of chartists according to this criterion was 72 and the number of other market participants was 129 (exact numbers may differ slightly due to incomplete replies). The achieved university level compounds graduation from university as well as from university of applied sciences.

The χ^2-test exploits not only the aggregated figures being presented here, but all available information.