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# 'Manna from heaven': does the presence of central banks make technical analysis profitable?

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Profitability of technical-analysis strategies has been explained with reference to central-bank intervention in markets (Neely 1998; LeBaron 1999; Saacke 2002). I argue that central-bank intervention is a market shock which leads to a generation of trends, making technical analysis profitable. Looking at empirical evidence from the Indian foreign-exchange market, I find returns calculated for the entire period are consistently and substantially higher than when intervention periods are removed. Thirteen out of the 15 strategies demonstrate higher returns with intervention periods included, compared to without intervention periods. The Kolmogorov–Smirnov sample tests show statistically significant differences in the returns between the entire period and the without-intervention period for four strategies, which is confirmed by bootstrap estimation. The paper contributes first by including actual trading strategies in the empirical testing of profitability of technical analysis and second by emphasizing the efficacy of technical analysis rather than the action of the central bank itself in explaining profitability, in a departure from the existing literature.

**Keywords:** central bank intervention, technical analysis, profitability of trading strategies, Reserve Bank of India

JEL codes: E44, E58, F31

# 1 INTRODUCTION

Traders concur on the profitability of technical analysis strategies, in spite of the deep academic distrust of it. If a random walk holds, the possibility of excess returns out of technical analysis strategies is ruled out (Fama 1998). However, a host of empirical studies have shown that technical analysis is profitable and generates excess returns, eschewing the academic negation of it (Pinches 1970; Surajaras/Sweeney 1992; Levich/Thomas 1993; Menkhoff/Schlumberger 1995; Neely et al. 1997; LeBaron 1999; Saacke 2002; Menkhoff/Taylor 2007). If technical analysis is indeed profitable, what explains its profitability? I contend that central-bank intervention plays a role in generating trends which are better interpreted by technical analysis strategies. I examine this for the Reserve Bank of India, India's central bank, which consistently intervenes in the market to contain volatility. Using daily data from the Indian foreign-exchange market, it is seen that technical analysis strategies yield greater profitability in the presence of central-bank intervention.

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The presence of the central bank does lead to unexpected and (unexplained?) gains in the market, much like 'manna from heaven.'

My findings are in conformity to an increasing literature in recent years showing that the profitability of technical analysis can stem from the presence of central-bank intervention in the market, put by LeBaron (1999: 137) as: 'Federal Reserve activity has something to do with the observed predictability.' Identifying periods of intervention, I calculate the returns generated from 15 technical analysis strategies over a period of two years, 2015–2017, on a daily frequency. To address the unavailability of daily data on intervention in the Indian market, data on big deals by public-sector banks in the foreign-exchange market are employed, through which the central bank carries out its intervention. The returns calculated for the entire period are substantially higher than when intervention periods are removed. Thirteen out of the 15 strategies demonstrate higher returns in the presence of intervention compared to without intervention periods. Further, the Kolmogorov–Smirnov test is used to compare the mean returns between the full sample and the sample without intervention period for the four strategies, which is confirmed by bootstrap estimation.

To answer why intervention should lead to the increased profitability of technical analysis strategies, I look at intervention by the central bank as a shock in the market. The shock in the market generates new information leading to the creation of trends in the market. Given the suitability of technical analysis indicators in understanding trend creation, brought about by the reaction of market participants to new information, technical analysis strategies work well during such random shocks. This can help explain the increasing empirical evidence on profitability in the presence of central-bank interventions. I differ from LeBaron (1999) in focusing on the efficiency of technical analysis strategies in understanding market psychology, and not on the central bank's actions. Evidently, technical analysis can interpret the central bank's actions and market reactions to it well enough to generate substantial profits.

The profitability of technical analysis is empirically proven and supported by anecdotal evidence from traders. Why should technical analysis be profitable if markets do indeed follow a random walk? If efficient market hypothesis works, it means that the incorporation of information and prices rules out the possibility of abnormal profits. However, in the presence of shocks to the macroeconomic system, I contend that the move away from efficiency would make technical analysis more profitable. In cases where the trend-following indicators work well for technical analysis, the creation of trends during intervention would lead to profitability of technical analysis indicators.

I add to the literature in two important ways. First, along with simple technical strategies usually used for empirical testing, I introduce complex strategies popular with traders to bring it close to the real-life trading scenarios. Second, I explain the profitability of the technical analysis strategies with reference to central-bank intervention as a random shock in the market. In a departure from earlier studies which placed the onus on the central bank for such profits being generated (LeBaron 1999), I argue that it may be the efficiency of technical analysis in reading signals from the central bank and the reaction to it, rather than the actions of the central bank itself which may be responsible for such a distinct increase in profitability when intervention periods are included.

## 2 THEORETICAL BACKGROUND

Technical analysis is the ability to forecast price movements based on qualitative and quantitative study of historical price data. Strategies developed either from visual analysis of graphs or statistical analyses of price patterns are used to forecast future prices. This contradicts the very heart of the random walk hypothesis. If a random walk holds, consequential changes in prices are random and therefore the forecasting of prices cannot be done 'in any meaningful way' (Fama/Blume 1966: 226). Fama/Blume (ibid.) point out that with the random walk holding in the financial markets, any technical analysis strategy cannot outperform a buy-and-hold strategy. If markets are efficient, prices at any given point in time correctly estimate its intrinsic value based on all information available until that point in time. If, with new information coming, the changes in prices behave in a random manner or are distributed independently as a random variable (Pinches 1970), the forecasting of future prices is largely ruled out.

In its narrow variant, random-walk theory postulates that future price movements cannot be predicted on the basis of past price data alone. In the broader sense, the random walk points out that present prices already reflect all past public information so that there is no scope for predicting future prices on the basis of history (ibid.). Following the seminal work of Meese/Rogoff (1983), it is held that the random walk exists in forex markets.

However, if the success of technical analysis comes from understanding under-reaction or over-reaction to information as sentiment sways the market, it does not violate market efficiency. For example, Fama (1998) points out that if over-reaction to the market is matched by under-reaction at some in time, it would suggest efficiency exists over the longer run. Menkhoff/Taylor (2007) point to the belief among traders that technical analysis can represent changes in market psychology. If fundamental factors cannot reflect changes or swings in sentiment, prices will not reflect all information. Prices may be over-reacting or under-reacting to new information from random shocks in the market. Over-reaction or under-reaction reflects market sentiment, interpreted well by technical analysis. Trend-following indicators can then be successful if market participants place a significant value on psychological influences (Menkhoff/Taylor 2007).

Are technical analyses self-fulfilling? If traders are confident on the ability of technical analysis indicators in interpreting psychological biases, logically technical analysis will be self-fulfilling. For this to happen, however, the same kinds of signals must elicit the same responses from traders, so that herd behavior ensues. However, given the wide variety of technical analysis rules, it is hardly plausible that they would generate uniform signals. This rules out the possibility of self-fulfilling movements generated in the market as it is unlikely that all traders trading at the same time reach the same interpretation and therefore take similar long or short positions.

The earliest empirical studies on the profitability of technical analysis indicators questioned the success of technical analysis strategies in the presence of the random walk. Brock et al. (1992) showed, using technical analysis based on filter techniques, that profit can be generated substantially in excess of buy-and-hold returns. Later studies confirmed that technical analysis served as an important tool in the hands of market practitioners in enabling effective trading decisions (Pinches 1970; Surajaras/Sweeney 1992; Menkhoff/Schlumberger 1995; Neely et al. 1997; LeBaron 1999; Saacke 2002; Menkhoff/Taylor 2007).

Moreover, Silber (1994), Szakmary/Mathur (1997), and Neely (1998) have all extended evidence that the presence of intervention is strongly associated with profits from technical analysis indicators. Neely (1998) points out that official interventions are usually during periods of sharp market movement, that is, when markets are trending, which also make technical analysis profitable. The analysis of Bundesbank interventions with high-frequency data (Frenkel/Stadtmann 2004) and daily data (Neely/Weller 2001) show that these rules are most profitable on the day before interventions take place. LeBaron (1999) points out that central-bank intervention would introduce noticeable trends in exchange-rate movement making it possible for market participants to gain from trading. The strongest explanation of

profitability of technical analysis strategies in the presence of central-bank intervention comes as the generation of trends post-intervention (Saacke 2002).

The presence of the central bank in the market leads to different reactions from market participants. As the central bank intervenes, the participants will adjust their trading positions, keeping in view the central bank's actions. In this case, the central bank's action can be identified as a market shock, which will lead to a change in the market movement. Again, central banks intervene to curb volatility following an exogenous shock and in this case too the exchange-rate adjustment would lead to trend creation. The success of technical analysis indicators in this environment comes from the ability to recognize trend creation. The basic premise of technical analysis is that the market moves in trends which can be recognized through suitable indicators.

Technical analysis indicators are largely trend-following. Indicators based on moving averages try to understand the start of a new trend by comparing the present price movement to longer-term averages. Divergence of prices from the longer-term averages suggests the existence of trends in the market. Momentum technical indicators, by seeing the rate of price change, try to get an early indication of the trend change. If central-bank activity leads to trend generation, it is contended that technical analysis indicators would be able to recognize the same and thereby generate excess returns.

I test the profitability of technical analysis indicators in the presence the Indian central bank, the Reserve Bank of India (RBI). The RBI intervenes in the Indian forex market, largely to keep the managed float stable (RBI 2013; Roy Trivedi 2019). The creation of a market shock when the central bank intervenes, I argue, should lead to greater profits from technical analysis in the presence of intervention. While a host of studies have looked at the profit-ability of technical analysis indicators in the presence of intervention, they have used only basic technical analysis strategies like moving-average indicators. I add to the literature by bringing, in addition, a host of strategies covering moving averages, momentum, and volatility indicators. While moving averages are helpful to identify the trend after it has been in motion for some time, momentum indicators by capturing the incremental changes in price movement lead to identification of trend earlier.

#### 3 DATA AND METHODOLOGY

Data on exchange rates has been taken from the Cogencis trading platform (Cogencis Information Services 2015) on a daily frequency. Data on interest rates are obtained from the RBI and Federal Reserve database. Intervention data by the RBI are not available on a daily basis. Intervention data would lose granularity if we took it on a monthly basis; therefore it is very important to take a proxy of intervention at the daily level. As a proxy for daily intervention, I use data on big deals by public-sector banks as the RBI intervenes through the big public-sector banks in the Indian market. Intervention in the Indian market is thus secret (Roy Trivedi 2019). This data has also been taken from the Cogencis trading platform (Cogencis Information Services 2015), which reports the 'Key deals in the Indian Foreign Exchange market,' detailing which banks groups have bought or sold in the Indian foreign-exchange market. Table 1 shows a sample of information taken from Cogencis. It shows the key deals in the Indian foreign-exchange market on Tuesday 3 January 2017. It is reported that a large state-owned bank was buying dollars upwards of 68.05 rupees.

I take this to be proxy for central-bank intervention. A criticism of this methodology is that the big deals reported by public-sector banks could also be bank's own deals. There is no way to distinguish between the two. However, since intervention is secret, market

Bank	Dollar/rupee level	Dollars bought in the market in millions
Large state-owned bank	68.05 upwards multiple levels	Large
Bank	Dollar/rupee level	Dollars sold in the market in millions
UK-based bank Another UK-based bank; two US-based banks	68.13 upwards 68.06	Moderate Moderate

Table 1 Sample of news in Cogencis used for intervention data (Cogencis, Tuesday 3 January 2017, Mumbai): the key deals in India's foreign-exchange market by 1315 IST<sup>a</sup>

*Notes:* a. These deals are not officially available. The compilation is based on information provided by interbank dealers. Trading counterparties are withheld in some cases, unknown in most cases. *Source:* Compiled by ('Congencis Journalist name'), Congencis Information Services Ltd.

participants would consider any big deal by a public-sector bank as a possible contender for intervention, building up speculation around it. For the purpose of our paper, it therefore serves as a proxy variable, since it also acts as a *market shock*. Even if market participants interpreted wrongly any deal as central-bank intervention, markets would be impacted in the same way as in a case of real intervention. Therefore, the data on big deals serve well as a proxy for intervention given the unavailability of daily intervention data.

The daily data are mapped with intervention data (as proxied by the big deals of public-sector banks) in the foreign-exchange market. Fifteen technical analysis strategies, commonly used by traders, are chosen and profits from these strategies calculated on the historical data. Technical strategies are designed to generate buy-and-sell signals on the basis of qualitative or quantitative studies of the data. I detail below the technical analysis strategies used and methodology followed for calculations of returns in each case.

The moving average is one of the simplest and yet most powerful technical analysis indicators. The basic moving-average signals used commonly in empirical literature stipulate a buy (or sell) signal if prices are greater (or smaller) than the moving average.

Formally, for an exponential moving average (EMA) of  $\propto$  periods,

if 
$$P_t > EMA_t^{\alpha} : +1 \text{ (buy)}$$
 (1)

if 
$$P_t < EMA_t^{\alpha} : -1$$
 (sell) (2)

$$EMA_t^{\alpha} = EMA_{t-1}^{\alpha}(1-w_t) + P_t w_t, \tag{3}$$

where  $w_t = \frac{2}{\alpha + 1}$  and  $\alpha =$  number of periods.

And the EMA for period 1 is taken as the simple moving average (SMA):

if 
$$SMA_t = \frac{\sum_{t=1}^{t+\alpha-1} P_t}{\alpha}$$
. (3a)

A commonly used moving-average strategy is the double-crossover method using shorter- and longer-period moving averages. Double-crossover strategies generate trading signals depending on the position of the shorter- and longer-period moving average.

The shorter-period average follows the market closely while the longer period is the smoother indicator. Thus when the trend changes, the shorter-period average (following market action closely) will turn earlier than the longer-period average. If that is so, a downtrend will be indicated by the shorter-run average  $\alpha^1$  crossing the longer-run average  $\alpha^2$  from above. An uptrend is denoted by the shorter-run average,  $\alpha^1$  crossing the longer-run average  $\alpha^2$  from below.

$$EMA_{t-1}^{\alpha^{1}} < EMA_{t-1}^{\alpha^{2}} \quad \text{and} \quad EMA_{t}^{\alpha^{1}} > EMA_{t}^{\alpha^{2}} : +1 \text{ (buy)}$$
(4a)

$$EMA_{t-1}^{\mathbf{x}^1} > EMA_{t-1}^{\mathbf{x}^2} \quad \text{and} \quad EMA_t^{\mathbf{x}^1} < EMA_t^{\mathbf{x}^2} : -1 \text{ (sell)}$$
(4b)

The addition of one more moving average is frequently done to get a confirmation on the signals, called the triple-crossover strategy. In this case, three moving averages,  $\alpha^1, \alpha^2$ , and  $\alpha^3$ , are used, where  $\alpha^1 < \alpha^2 < \alpha^3$ :

$$EMA_{t-1}^{\alpha^2} < EMA_{t-1}^{\alpha^3} \quad \text{and} \quad EMA_t^{\alpha^2} > EMA_t^{\alpha^3} \quad \text{and} \\ EMA_t^{\alpha^1} > EMA_t^{\alpha^2} > EMA_t^{\alpha^3} : +1 \text{ (buy)}$$
(5a)

$$EMA_{t-1}^{\alpha^2} > EMA_{t-1}^{\alpha^3} \quad \text{and} \quad EMA_t^{\alpha^2} < EMA_t^{\alpha^3} \quad \text{and} \\ EMA_t^{\alpha^1} < EMA_t^{\alpha^2} < EMA_t^{\alpha^3} : -1 \text{ (sell)}.$$
(5b)

While using historical data for back-testing strategies it is important to avoid the lookahead bias (Chan 2009). The look-ahead bias comes from incorporating in the present time period any transaction requiring any future information. For example, if closing prices are used to calculate moving averages, signals generated by a double-crossover method in any period are based on the closing prices of the same period. The signal generated by the double-crossover strategy would necessarily be available after the end of the period. Transactions on the signal therefore can happen only after the period, that is, in the next period. For calculating the transaction prices, then, taking the close price of the same period would lead to look-ahead bias. Instead, the next period's open, close, or average should be taken.

The first four strategies used in the paper, R1, R2, and R3, are variants of the movingaverage strategy. R1 is the returns calculated from applying the double crossover strategy, with a 5- and 10-period moving average. R2 is the returns calculated from applying the double-crossover strategy with a 10- and 20-period moving average. R3 uses a double-crossover strategy (5- and 10-period) with a 1 percent filter, commonly used by traders.

Whipsaws occur when the crossover strategy generates false signals which are reversed within a few periods. This means that a buy (sell) signal is generated but the market turns down (up), swiftly leading to losses for the trader. Such whipsaws are common in sideways-moving markets or when there is high volatility in the market. These trades are not profitable for the traders as the trend is not correctly recognized. To address this problem, the filter technique is frequently used to generate better signals. In this case the trader will take the buy (sell) signal as confirmed if the price holds above (below) a certain percentage of the price given at the time the signal was generated.

In each of the above cases mentioned, the transaction price (TP) is the open price in the next period as the strategy is assumed to materialize into a decision in the next period and returns are calculated accordingly. Returns are calculated as shown below, assuming a buy position is held until the next sell signal, and the position is short until the next buy signal. In other words, a trader will remain long on a strategy

until s/he gets an opportunity to sell, and similarly s/he will remain short till s/he gets an opportunity to buy back the security.

For a buy decision,

$$R_t = 1 - \frac{TP_t}{TP_{t-1}}.$$
(6a)

And for a sell decision,

$$R_t = \frac{TP_t}{TP_{t-1}} - 1. \tag{6b}$$

R4 calculates excess or dynamic returns for the double-crossover strategy using 5- and 10-period moving averages with a 5 percent filter. R5 calculates excess or dynamic returns for the double-crossover strategy using 10- and 20-period moving averages. R6 calculates excess returns for the triple-crossover strategy. In calculating the returns, it does not take the transaction price but considers a 'buy' position as long (+1) and a sell position as short (-1).

Excess returns for each period adjusted for interest-rate differential (Saacke 2002) is calculated as

$$R = \log\left(\frac{P_t}{P_{t-1}}\right) - \frac{r - r^*}{260},$$
(7)

where  $r - r^*$  is the interest-rate differential between the foreign and the home country (\*), and  $P_t$  is the exchange rate at period *t* (closing price), defined as the number of units of home-country currency for one unit of foreign-country currency.

R7 brings in another simple strategy, comparing prices with the EMA  $^{20}$  (where the superscript denotes the number of periods) to generate trading signals and using normal returns for calculating the profits from the strategy. If there is a rise in price, the return will be positive, while a fall in price will generate negative returns. Therefore the 'buy' decision will be taken to be successful if it is followed by a price rise, and the 'sell' decision will be taken to be successful if it is followed by a fall in price. As the dummy for 'buy' or long position is +1, profits would be positive only if the returns are positive for the given period. Similarly a 'sell' decision or short position (-1) would generate positive profits when the return is negative. R8, R9, and R10 compare prices with EMAs <sup>5</sup>, <sup>10</sup>, and <sup>20</sup> respectively, using excess returns for calculating profits from the said strategies.

R11 and R12 use the volatility-based indicator, Bollinger bands, to calculate the trading profits. Bollinger bands plot the upper and lower ranges for price movement based on the volatility of the series. The upper and lower bands are constructed at  $\pm 2$  standard deviation around the mean as follows:

$$BB_{UB} = MA^{\alpha} + 2\sqrt{\frac{\left(\sum_{t=1}^{\alpha} P_t - \bar{P}\right)^2}{\alpha}}$$
(8a)

$$BB_{LB} = MA^{\alpha} - 2\sqrt{\frac{\left(\sum_{t=1}^{\alpha} P_t - \bar{P}\right)^2}{\alpha}}.$$
(8b)

The above formulae underline the logic behind Bollinger bands: if markets follow a standard normal distribution, Bollinger bands will cover 95 percent of the market movement. The difference between the upper band and the lower band (bandwidth) is an indicator of the extent of volatility of the series. The Bollinger bands strategy requires determining the volatility of the series as it is expected that periods of high volatility, represented by higher bandwidth, are followed by periods of low volatility, with the bands becoming closer. In market parlance this is called as a 'squeeze.' A squeeze is generally followed by a period of increased volatility.

R11 uses a Bollinger band strategy whereby decisions are taken in periods of higher volatility. The strategy is framed in the following way. I differentiate periods of high and low volatility based on the bandwidth. A variable is assigned the dummy value, 1, when the difference between the upper band and lower band exceeds the 5-period average difference. Otherwise the dummy takes a value of 0. Once the price reaches the upper band during a period of high volatility, or as the Bollinger bands expand, we expect prices to go down. In this case a 'sell' decision should be taken. Similarly, once prices reach the lower band during a period of expanding volatility, they are expected to go up; in this case a 'buy' decision is taken. The strategy is assumed to materialize into a decision the next day at open prices and returns are calculated accordingly as in the cases of first three strategies.

R12 uses a squeeze for trading: in periods of low volatility (that is, volatility < average volatility), if the high of the day is greater than the upper band, a sell signal is generated as we expect prices to fall. If the low of the day is lower than the lower band we expect prices to go up from there, and a buy strategy is generated. Similar to the previous strategy, the transaction price is taken to the open price of the next period and returns are calculated accordingly. I therefore distinguish between high and low volatility for Bollinger bands trading strategy design.

The next group of strategies use momentum-based indicators. The momentum indicator compares the price movement in the present period with reference to a certain period in the past. The most basic momentum indicator is the rate of change (ROC). It is given by the simple formula:

$$ROC = \frac{P}{P_t} * 100,\tag{9}$$

where P is the price today and  $P_t$  is the price t days earlier. I take ROC to be 10 periods, in conformity to the moving averages used. As I have used 5-, 10-, and 20-period averages, the 10-period ROC will help in comparisons between momentum and the moving-average indicator. Multiplying it by 100 converts it to a comparable figure. This strategy requires a long position to be taken if the ROC value is above 100 and a short position to be taken if the value calculated is below 100. Normal returns are used to calculate profits from the strategy R13.

The relative strength index (RSI) indicator forms the basis of the next two strategies. The RSI, like any other momentum indicator, gives the strength in the market. It is given by

$$RSI^{\alpha} = 100 - \frac{100}{1 + RS},\tag{10}$$

where RS = up closes/down closes over a period of  $\alpha$  periods. In this paper, using standard market convention, I take  $\alpha$  to be 14 periods.

The RS will show higher values if there are more up closes than down closes. Up closes are marked if prices in a said period are greater than in the previous period. The greater the

value of the RS, the smaller is the second term on the right-hand side of the equation and hence the higher is the value for the RSI. Commonly values of the RSI over 70 are interpreted as overbought conditions in the market, implying markets are overheated. Similarly as the RS falls in value, the RSI also reflects the same. Values of the RSI below 30 are represented as oversold conditions in the market. The midpoint line in any momentum indicator is taken to generate signals as the indicator crosses above and below it. R14 uses a simple strategy of going long if the RSI crosses over 50 and going short if the RSI goes below 50. Excess returns are used to calculate profits in this case.

Divergence is another commonly used strategy by traders. Divergence happens when prices and the RSI move in opposite directions. In an uptrend, if prices are moving up and the RSI is moving down, it is called a negative divergence, while in a downtrend, such a divergence is called a positive divergence. As the RSI is an indicator of market strength, a divergence shows that while the market is moving up (down), the strength to move in that direction is lost. A negative (positive) divergence generates a sell (buy) signal. The transaction price taken is the next day's open price and accordingly the returns from this strategy are calculated.

Table 2 gives a brief description of all strategies along with the average profits for each of them. Strategies 1–10 are moving-average based, 11 and 12 are volatility-based, and 13 to 15 are momentum-based.

# 4 RESULTS AND DISCUSSIONS

The paper looks at the profitability of technical analysis indicators in the presence of centralbank intervention by presenting a unique data set for daily intervention data. Tables 3 and 4 give the descriptive statistics for the exchange rate in various sub-samples. Table 3 compares the average and standard deviation of the exchange rate in the full sample, excluding intervention periods and only intervention periods. The full sample consists of 640 data points, of which 442 periods are without intervention and 198 have intervention (as proxied by large deals by public-sector banks). The average exchange rate (close) for the full sample is 65.59 while the without-intervention periods have noted a slightly higher rate of 65.65 and the periods with intervention a slightly lower rate of 65.46. Importantly, the periods with intervention have registered a significantly higher volatility, with a standard deviation of 2.03, compared to the other two samples. The full sample has a standard deviation of 1.85 and periods without intervention have a standard deviation of 1.76.

Table 4 compares the exchange rate in the various intervention samples. 161 out of the 198 periods of intervention had public-sector banks buying dollars (expected to be on behalf of the central bank), so the major interventions in these periods was on the buy side. There are 24 sell-side interventions and 13 are reported to have interventions on both the buy and the sell side. The volatility of periods with intervention on the buy side (5.18) is more than twice the volatility recorded in other periods (1.9 in sell-side interventions and 1.52 in both-side interventions, respectively). Intervention on both sides have the least volatility.

The findings presented in Table 3 and 4 are in line with the literature on central-bank intervention. The RBI generally follows a 'leaning against the wind' policy in the Indian forex market (RBI 2013; Roy Trivedi/Apte 2016). As most of the interventions noted are on the buy side, the exchange rate is expected to be appreciating during the intervention periods, as seen in our sample. The average exchange rate during intervention periods stands at 65.46 as compared to the higher rate of 65.65 in periods without intervention. Again the RBI strongly intervenes to stem volatility (Roy Trivedi/Apte 2016), which can explain the higher volatility noted during the intervention period. However, it must be noted here that volatility may be both a cause and an effect of intervention (Roy Trivedi 2019). While the

		0				
Strategy	Broad type	Brief description	Calculations of returns is based on	Full sample average profits	Excluding intervention average profits	D (full sample > excl. int.)
1		Double crossover, 5 and 10 periods	E	0.043%	0.035%	1
2		Double crossover, 10 and 20 periods	I ransaction prices (open price of the next neriod)	0.004%	0.008%	0
$\mathcal{C}$		Double crossover, 5 and 10 periods with 1% filter		0.014%	0.000%	1
4	Moving agreed	Double crossover, 5 and 10 periods with 5% filter		0.014%	0.011%	1
5	based strategy	Double crossover, 10 and 20 periods	Excess returns	0.006%	0.006%	1
9		Triple crossover, 5, 10, and 20 periods		0.016%	0.00%	1
7		Simple crossover (EMA <sup>20</sup> )	Normal returns	0.070%	0.057%	1
8		Simple crossover (EMA <sup>5</sup> )		0.233%	0.206%	1
6		Simple crossover (EMA <sup>10</sup> )	Excess returns	0.192%	0.166%	1
10		Simple crossover (EMA <sup>20</sup> )		0.201%	0.177%	1
11	Volatility based	High volatility period strategy	Transaction prices (open	-0.008%	-0.002%	0
12	(DUILINGEL DALIUS)	Low volatility period strategy	price or rife riext perious	0.051%	0.040%	1
13		Rate of change (ROC)	Normal returns	0.050%	0.042%	1
14	Momentum	Relative strength index (RSI)	Excess returns	0.135%	0.066%	1
15	based strategy	RSI divergence	Transaction prices (open price of the next period)	0.074%	0.067%	1

Table 2 Description of strategies

Source: Author's estimates.

		Average			Std dev.					
	Intervention (buy side: 161)	Intervention (sell side: 24)	Intervention (both sides: 13)	Intervention (buy side: 161)	Intervention (sell side: 24)	Intervention (both sides: 13)				
Open High Low Close	65.01 65.12 64.91 65.02	66.1 66.2 65.9 66.0	66.36 66.48 66.25 66.39	5.18 5.19 5.17 5.18	1.9 1.9 1.9 1.9	1.57 1.53 1.58 1.52				

Table 3 Exchange rate: without intervention, with intervention, and full sample

Source: Author's estimates.

Table 4 Exchange rate in intervention period different sub-samples

		Average			Std dev.					
	Without intervention (442)	With intervention (198)	Full sample (640)	Without intervention (442)	With intervention (198)	Full sample (640)				
Open High Low Close	65.67 65.76 65.55 65.65	65.45 65.56 65.34 65.46	65.60 65.69 65.49 65.59	1.76 1.76 1.76 1.76	2.03 2.03 2.03 2.03	1.85 1.85 1.85 1.85				

Source: Author's estimates.

endogeneity issue is a gray area in intervention studies, it has been shown that intervention sees a jump in the volatility in the forex market (Chari 2007; Roy Trivedi 2019). This explains why the intervention period shows a substantially higher volatility than other periods.

Table 5 gives the main results of comparing the returns of the strategies from the full sample and the sample excluding intervention. As in LeBaron (1999), I exclude intervention periods to see whether the full sample returns are greater than the sample excluding intervention, or whether removing intervention periods leads to a fall in profitability for the strategies. I see that in all but two strategies (strategies 2 and 11), the average profits of the full sample are greater than those of the sample without intervention. The average volatility of the full sample is also higher for all strategies than with intervention excluded, underlining that while intervention leads to increased profitability, the returns are more volatile. The highest profits are noted for strategy 8, followed by 9 and 10, as noted in Tables 5, 6, and 7. The results suggest that the presence of central-bank intervention leads to a substantial increase in profits for technical analysis strategies. This holds for a broad range of strategies encompassing moving-average strategies, volatility indicators, and momentum indicators. Plotting the difference between returns for the entire period and prices excluding intervention periods in Figure 1, I see that highest difference in profits is noted for momentum and moving-average-based strategies.

Further, I conduct two sample Kolmogorov–Smirnov tests to see if the difference in the returns between the samples are significant. The results are reported in Table 8. The first line tests the hypothesis that returns (from a particular strategy) for group 1 (that is, with intervention) contain smaller values than for group 2 (without intervention). The second line tests the hypothesis that returns for group 1 (that is, with intervention) contain larger values than for group 2 (without intervention). The *p*-value, as we can see

		Mean		Std dev.					
Strategy	Full sample	Excluding intervention	D (full sample > excl. int.)	Full sample	Excluding intervention	D (full sample > excl. int.)			
1	0.043%	0.035%	1	0.351%	0.298%	1			
2	0.004%	0.008%	0	0.297%	0.259%	1			
3	0.014%	0.000%	1	0.621%	0.534%	1			
4	0.014%	0.011%	1	0.204%	0.186%	1			
5	0.006%	0.006%	1	0.715%	0.562%	1			
6	0.016%	0.009%	1	0.575%	0.447%	1			
7	0.070%	0.057%	1	0.242%	0.208%	1			
8	0.233%	0.206%	1	2.395%	1.975%	1			
9	0.192%	0.166%	1	2.399%	1.979%	1			
10	0.201%	0.177%	1	2.398%	1.978%	1			
11	-0.008%	-0.002%	0	0.293%	0.243%	1			
12	0.051%	0.040%	1	0.267%	0.233%	1			
13	0.050%	0.042%	1	0.246%	0.211%	1			
14	0.135%	0.066%	1	2.394%	1.977%	1			
15	0.074%	0.067%	1	1.181%	0.937%	1			

Table 5 Comparison of returns in full sample and periods without intervention

Source: Author's estimates.

	Excluding interventi points: 44	on (number of data 42, 69%)	Only intervention (number of data points: 198, 31%)			
Strategy	Mean	Std dev.	Mean	Std dev.		
1	0.035%	0.298%	0.011%	0.198%		
2	0.008%	0.259%	-0.001%	0.181%		
3	0.000%	0.534%	0.014%	0.317%		
4	0.011%	0.186%	0.011%	0.186%		
5	0.006%	0.562%	0.000%	0.441%		
6	0.009%	0.447%	0.007%	0.362%		
7	0.057%	0.208%	0.013%	0.129%		
8	0.206%	1.975%	0.027%	1.359%		
9	0.166%	1.979%	0.026%	1.359%		
10	0.177%	1.978%	0.024%	1.359%		
11	-0.002%	0.243%	-0.005%	0.164%		
12	0.040%	0.233%	0.011%	0.133%		
13	0.042%	0.211%	0.008%	0.130%		
14	0.066%	1.977%	0.069%	1.353%		
15	0.067%	0.937%	0.007%	0.719%		

Table 6 Comparison of returns without intervention and only intervention periods

Source: Author's estimates.

from Table 8, is statistically significant for four strategies (8, 9, 10, and 14). In all four cases, I reject the hypothesis of group 1 (that is, with intervention) containing smaller values than group 2 (without intervention). The *p*-value combined is also significant for all four strategies at the 1 percent level of significance (for strategies 8, 9, and 10) at the 10 percent level of significance (for strategy 14). To add to the robustness of the

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	Highest volatility in	Buy	Both	Buy	Buy	Both	Sell	Both	Buy	Buy	Buy	Selİ	Both	Both	Both	Both
Std dev.	Intervention ] (both sides: 13)	0.098%	0.406%	0.588% ]	0.000%	0.977%	0.627%	0.283% ]	1.767% ]	2.122%	2.318%	0.000%	0.401%	0.282% ]	2.545% ]	1.399%
	Intervention (sell side: 24)	0.000%	0.221%	0.000%	0.000%	0.726%	0.778%	0.197%	2.458%	2.458%	2.372%	0.323%	0.089%	0.199%	2.491%	1.374%
	Intervention (buy side: 161)	0.377%	0.357%	0.628%	0.159%	0.850%	0.658%	0.244%	2.470%	2.472%	2.473%	0.288%	0.274%	0.247%	2.462%	1.313%
	Highest return in	Buy	Both	Both	Buy	Selİ	Both	Both	Both	Both	Both	Sell	Both	Both	Both	Both
Mean	Intervention (both sides: 13)	-0.028%	0.126%	0.170%	0.000%	-0.038%	0.181%	0.052%	1.860%	1.442%	1.100%	0.000%	0.087%	0.057%	0.321%	0.067%
	Intervention (sell side: 24)	0.000%	-0.040%	0.000%	0.000%	0.029%	0.016%	0.035%	0.260%	0.260%	0.695%	0.069%	0.019%	0.023%	-0.127%	-0.303%
	Intervention (buy side: 161)	0.040%	0.014%	0.068%	0.012%	-0.001%	0.041%	0.048%	0.096%	0.090%	0.025%	-0.025%	0.047%	0.033%	0.221%	0.065%
	Strategy	1	2	e S	4	Ś	9	7	8	6	10	11	12	13	14	15

Source: Author's estimates.



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Figure 1 Difference between returns (including and excluding intervention periods)

	1	0		1	
Strategy	Group	D	P-value	Exact	Bootstrap ASL ( <i>p</i> -value)
	0	0.0333	0.749		
1	1	-0.0066	0.989		N/A
		0.0333	0.999	0.997	
	0	0.0358	0.716		
2	1	-0.0137	0.952		N/A
		0.0358	0.996	0.993	
	0	0.0055	0.992		
3	1	-0.0164	0.932		N/A
		0.0160	1.000	1.000	
	0	0.0046	0.994		
4	1	-0.0007	1.000		N/A
		0.0046	1.000	1.000	
	0	0.0258	0.840		
5	1	-0.0203	0.898		N/A
		0.0258	1.000	1.000	
	0	0.0175	0.924		
6	1	-0.0142	0.949	1 000	N/A
		0.01/)	1.000	1.000	

Table 8 Two sample Kolmogorov-Smirnov tests and bootstrap estimations

(continues opposite)

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Strategy	Group	D	P-value	Exact	Bootstrap ASL ( <i>p</i> -value)
	0	0.0820	0.173	1	
7	1	-0.0005	1.000		N/A
		0.0820	0.345	0.323	
	0	0.1658	0.001		0.00
8	1	-0.0557	0.446		
		0.1658	0.002	0.001	
	0	0.1565	0.002		0.00
9	1	-0.0580	0.416		
		0.1565	0.003	0.003	
	0	0.1769	0.000		0.00
10	1	-0.0373	0.696		
		0.1770	0.001	0.000	
	0	0.0144	0.947		
11	1	-0.0082	0.983		N/A
		0.0144	1.000	1.000	
	0	0.0443	0.600		
12	1	-0.0274	0.822		N/A
		0.0443	0.960	0.948	
	0	0.0714	0.265		
13	1	-0.0148	0.944		N/A
		0.0714	0.519	0.492	
	0	0.1314	0.011		0.00
14	1	-0.0851	0.151		
		0.1314	0.022	0.02	
	0	0.0568	0.431		
15	1	-0.0543	0.464		N/A
		0.0568	0.794	0.766	

Table 8 (continued)

Source: Author's estimates.

findings from the Kolmogorov–Smirnov test, I calculate the achieved significance level (ASL) of the test statistic by using bootstrap estimations with 1000 resampling. The samples are drawn with replacement making it a Markov process (Schmuland 2017). The ASL calculated for the four strategies (8, 9, 10, and 14) for which the Kolmogorov–Smirnov test showed significant difference in means is presented in the last column of Table 8. I see the ASL is significant for all four strategies. The results are also in line with the graphical analysis of Figure 1, where the differences are highest for strategies 8, 9, 10, and 14.

What explains the profitability of such strategies? It implies that as a central bank intervenes in the market, it leads to new movement emerging as well as a reorientation of trading

strategies. The departure of markets from efficiency as seen in over-reaction or under-reaction to information is interpreted better with technical-analysis strategies. Over-reaction or underreaction thus reflect market sentiment, interpreted well by technical analysis (in which market participants place a significant value on psychological influences).

The findings suggest that central-bank intervention is suggestively coincident with trend generation in the market, which can explain why more moving-average-based strategies are found to be doing well during interventions. Tables 5 and 6 both show that the simple strategies 8, 9, and 10 have significantly high returns during intervention periods. Moving-average strategies recognize trends that are already ongoing as compared to momentum indicators which try to pre-empt the change of trend. In market parlance, therefore, momentum indicators are popular as 'leading' indicators compared to 'lagging' moving-average-based indicators. The intervention periods must therefore be coinciding with the period where the trend has already begun. Thus, the presence of intervention and increased profitability during such a period from moving-average indicators require the trend to be already in motion. Table 7 compares the returns from different intervention periods. I see that periods characterized by interventions on both sides of the market lead to greater profitability as well as to volatility of returns. This means that there is a trend generation associated with these periods which can explain the increased profits. Interventions on the buy side also have seen sharp volatility in technical-analysis returns during the period under consideration.

This result is similar to the findings in economic literature underlining the creation of sharp market movements with central-bank intervention, and higher profitability of technical-analysis indicators during these periods (Neely 1998; LeBaron 1999; Neely/Weller 2001). Are profits from using technical-analysis strategies in the presence of central-bank intervention 'manna from heaven': unexpected or windfall gains? The analogy is used to highlight the substantial difference in profits seen during periods of intervention. These profits arguably are crucial for many trading portfolios. However, what is the reason behind the significantly greater profitability during these periods? We emphasize the trend generation caused by the market shock.

Trend is nothing but the movement of prices in one direction. From a sideways and indecisive market move, the trend generated shows either the bears winning over the bulls, or the contrary. This requires a *market shock* leading to a change in the trading positions of the market participants. Central-bank intervention qualifies well as a market shock, given that central banks take care to use the signaling impacts of intervention effectively. For the Indian market, this is all the more true given the secret nature of intervention. The choice of the proxy variable used in this paper for intervention lends support to this argument. As news of big deals in the market is taken as a proxy for intervention, it is likely that many of these deals reported may be simply banks' own deals and not interventions by the central bank. However, for other market participants, there is an element of uncertainty when they see the big deals by public-sector banks, as they are unsure whether or not the central bank has really intervened. The big deals therefore will be seen as *market shocks* by other participants, as they are speculating whether or not the central bank has intervened through the publicsector banks. Accordingly, market participants will reorient positions leading to a change in market movement or an expected trend generation. Technical analysis thus sees an increased profitability with intervention by the central bank in the Indian forex market.

#### 5 CONCLUSION

The paper finds that central-bank intervention leads to higher profitability of technicalanalysis indicators in the Indian foreign-exchange market. The profits are unexpected,

windfall gains: 'manna from heaven' to the trading desks. We contend that the trend generation brought about by central-bank intervention or any other market shock is the reason behind this increased profitability. Analysing the behavior of technical-analysis profitability in the presence of market shocks would not only lead to a better understanding of foreign-exchange market dynamics but would also help in implementing appropriate policies.

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