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Technical analysis and central bank intervention in emerging currency markets

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Abstract

In this research we investigate the relationship between technical trading rule profits and central bank intervention for emerging market currencies. Our analysis is based on a sample of 21 emerging markets with a floating exchange rate regime over the period 1997-2007. First, we confirm the profitability of technical trading rules for emerging market currencies, which have also been documented in earlier studies. Next, we relate the profits to intervention, which is done in two parts. In the first part, we use reserves changes a proxy for intervention and perform regression tests. In the second part, we perform a case study for Peru and Turkey in which we use detailed data on central bank intervention. We exclude the periods in which the central banks intervene and analyze the profits after removal of intervention. The outcomes of the analyses lead to the conclusion that there is a plausible relationship between trading rule profits and central bank intervention for emerging market currencies.

Keywords: Emerging markets; Foreign exchange rates; Technical Trading; Central Bank Intervention

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1 Introduction

Extensive research has been done on the efficiency of foreign exchange markets for developed countries. In an efficient market, the exchange rate should reflect all information available to the public. Thus, it should not be possible to make trading profits on the basis of such information. Technical trading rules attempt to predict future movements in the price using the historical price information. There has been ample discussion about the usefulness of technical trading rules. The traditional answer, supporting efficient markets, is that we should not take technical analysis seriously because it relies upon the price history itself and not on fundamentals (Fama (1970)). However, it is extensively used in practice and studies find evidence of predictability, suggesting that the foreign exchange markets are not efficient, see for example Sweeney (1986), Levich and Thomas (1993), Neely, Weller and Dittmar (1997) and Menkoff and Taylor (2007).

A possible explanation for the profits of technical trading rules is that government interference is responsible for the inefficiency of foreign exchange markets (Sweeney (1986) and Dooley and Schafer (1976)). This is also supported by the fact that technical trading rules are less successful for equity and commodity markets, as there is no intervention in those markets (Silber (1994)). In particular, central banks may intervene by buying or selling a certain amount of a currency. Objectives of central banks to intervene, discussed in BIS (2005), include: to control the level of inflation or maintain internal balance; to maintain external competitiveness and stimulate economic growth; to prevent or handle unstable markets and crisis periods. To accomplish these goals, central banks can set exchange rate target levels, affect the level of foreign exchange reserves or reduce exchange rate volatility. Many central banks often intervene to reduce the volatility of exchange rate fluctuations. If this is the case, central banks may be willing to incur losses on their interventions. Trend following strategies can be profitable if central banks slow down the changes in the exchange rate by 'leaning against the wind', which is the behavior that they buy their currency when the exchange rate is (sharply) depreciating, and sell their currency when the exchange rate is (sharply) appreciating. This can cause trending behavior in the exchange rate, which can be detected by technical trading rules.

A substantial number of studies have analyzed the profitability of technical trading rules and central bank intervention for developed currency markets. The first paper investigating the relationship between central bank interventions and profitability of trading rules is Szakmary and Mathur (1997). They use changes in foreign exchange reserves as a proxy for intervention activity and set up conditions that represent leaning against the wind behavior. Their regression results indicate that for three out of five currencies, trading rule profits can be fully explained by leaning against the wind type of intervention by central banks. For the remaining two currencies, intervention partly explains the profits. An important paper supporting the intervention hypothesis is LeBaron (1999). He uses moving average rules and daily intervention data of the Federal Reserve and finds that, after removing the returns on the days where intervention occurred, profits are dramatically reduced and become insignificant. The results suggest that there is a relationship between trading rule profitability and central bank intervention and that technical traders can gain at the expense of central banks. Saacke (2002) confirms the results of LeBaron (1999) and he finds that intervention is profitable for central banks as well. In particular, the profits of central banks and traders are made over different time periods: in the short run, the direction of the exchange rate movement is inconsistent with the intentions of central banks (that is when the trading rules make profits), but in the long run the opposite is the case (when central banks eventually make profits). Further investigations have been done to examine if actually the interventions are the source of excess returns of technical trading rules. Neely and Weller (2001) compare the profitability of technical trading rules with intervention information incorporated and technical trading rules without such information incorporated. They find no evidence that (out of sample) trading rule profits can be improved by incorporating intervention information in the trading rules and conclude that intervention activity does not cause profits, but intervention tends to reverse strong and persistent trends in exchange rates. Neely (2002) investigates the timing of the correlation between intervention and the trading rule returns more closely, using higher frequency (intraday) data. The results show that the direction and timing of intervention and trading rule signals supports the fact that it is unlikely that interventions are the source of trading rule returns.

More recently, there is evidence that the profitability of technical trading rules for developed market currencies has been decreasing. Olson (2004) conducts tests with moving average rules for the period 1971 to 2000. He finds that trading rule profitability has declined for most currencies, suggesting that foreign exchange markets have become more efficient. Pukthuanthong-Le et al. (2007) find a similar pattern for data up until 2006. Neely et al. (2009) relate the declining profitability of trading rules over time with the Adaptive Markets Hypothesis. They find evidence that forces such as learning, competition and evolutionary selection pressures cause profits to decline. Pukthuanthong-Le and Thomas (2008) investigate several hypotheses for the profitability of technical trading rules, including the intervention hypothesis, for the period of 1983 to 2006. They follow the procedure of LeBaron (1999) by removing the returns on the day with intervention. For the entire period, they find a decline of profits after removing the returns around intervention days. However, the profits are still significant and therefore they conclude that the results do not support the intervention hypothesis. This may be due to the fact that the central bank interventions have declined in the recent period, except for Japan. The Federal Reserve for example, has not intervened since 2000. Instead, they conclude that the decline of trading rule profits supports the hypothesis that investors learn because of earlier publications and that the currency markets are weak-form efficient.

Most research on technical trading rules has been done on developed currency markets, and not much attention has been given to emerging markets. Partly this can be explained by the fact that until recently many emerging markets maintained a fixed or pegged exchange rate. By now, longer time series and a wider cross-section of emerging market currencies are available for emerging markets, making it possible to conduct a meaningful analysis of technical trading rules for these currencies. A limited number of studies have shown that, while technical trading rule profits have been declining for developed markets, they still appear to do well for emerging markets. Pukthuanthong-Le et al. (2008) illustrate for several emerging market currencies that technical analysis is profitable. De Zwart et al. (2009) investigate the technical trading rule profitability for 21 emerging markets currencies from the point where they became floating. They find profits for most of these currencies using Moving Average rules and Support and resistance rules.

The effectiveness of foreign exchange interventions in developed markets is questionable due to the small size of interventions relative to market turnover, as discussed in Canales-Kriljenko (2003). In case of emerging markets, the size of the intervention relative to the market turnover tends to be considerably larger, as the turnover in emerging markets is still small, see IMF (2007). Another reason why central bank intervention can be more effective in emerging markets is that the central banks may have a greater informational advantage over local participants on fundamentals, order flows and net open positions of traders, because the domestic markets are less sophisticated and have strict reporting conditions. This allows the central banks to time and conduct intervention such that it increases the market impact. Further, due to capital controls which restrict the accessibility to international capital markets, central banks in these countries may have more influence on the market.

No research however, has related the profitability of technical analysis to central bank intervention for emerging currency markets. The main purpose of this research is to fill this gap in the literature. Therefore, the main research question that we address is whether the profitability of technical trading rules can be explained by central bank interventions for emerging currency markets.

We investigate the possible relationship between central bank intervention and technical trading rule profits for 21 emerging market currencies relative to the US dollar from the point they were floating between January 1997 and June 2007. We consider different types of trading strategies to test whether the relationship between central bank intervention and trading rule profits differs across rules. The strategies are based on Moving Average rules and Support and Resistance rules. Because the availability of data is limited for a number of countries, we also construct a weighted portfolio over the currencies to have an impression of how technical trading rules generally perform in emerging markets. Next, we attempt to relate the returns of the trading strategies to central bank intervention. This is being done in two parts. In the first part, we use foreign exchange reserves as a proxy for intervention and adopt the procedure of Szakmary and Mathur (1997) by performing regression tests with trading rule returns as a dependent variable. In the second part, we follow the procedure in LeBaron (1999). Here, we use actual intervention data, and remove the returns on days on which intervention has occurred. As we only have intervention data available from Peru and Turkey, we perform a case study for these two countries. Further, we consider the problem of simultaneity, as other factors may drive both trending behavior of exchange rate and central bank intervention.

Our results can be summarized as follows. First, we confirm earlier results that technical analysis is profitable for emerging market currencies and at the same time, the profits on developed market currencies have declined in recent years. Further, we find that Moving Average strategies generally perform better than Support and Resistance strategies.

Second, the results for the analysis with a proxy for intervention indicate that leaning against the wind intervention helps explaining trading rule profits for a large number of countries. The results are stronger for Moving Average strategies than for Support and Resistance strategies, suggesting that Moving Average rules are more able to detect patterns in the exchange rate during intervention periods. Further, we find that the profits cannot be explained by macroeconomic variables.

Third, the results of our case study indicate that central bank intervention is associated with trading rule profits for Peru and Turkey. In case of Peru, we find that after removal of the returns on intervention days, the profits decrease substantially for both types of strategies. On the other hand, there are still profits left after the removal of intervention days in case of Turkey. The results also suggest that persistently intervening may introduce trends in the exchange rate which can be detected by technical trading rules, as we find evidence for Peru. Further, we find that removing the most volatile periods does not decrease the profits suggesting that volatility is not a common factor driving intervention and exchange rate predictability.

We conclude that a relationship between central bank interventions and technical trading rule profits in emerging currency markets is plausible.

The remainder of this paper is organized as follows. In section 2, we describe the different types of data we use in this research. In Section 3 we investigate the profitability of technical trading rules for emerging market currencies. In Section 4 we investigate the relation between those profits central bank intervention with regression tests, using changes in foreign exchange reserves as a proxy for intervention. In Section 5 we perform the case study for Peru and Turkey by removing returns on actual intervention days. In Section 6 we conclude.

2 Data

This section describes the data used in this research. We divide this in the following parts: Spot exchange rates and interest rates (Section 2.1), foreign exchange reserves (Section 2.2), foreign exchange intervention data (Section 2.3) and macroeconomic variables (Section 2.4).

2.1 Real exchange rates and interest rates

In this research we use daily foreign exchange rate series from emerging markets. The dataset described in this Section is identical to the dataset in De Zwart et al. (2009). We have spot exchange rate data available for 21 emerging market currencies around the world: From Latin-America we have the Argentine peso, Brazilian real, Chilean peso, Colombian peso, Mexican peso and Peruvian sol. From Asia, we have the Indian rupee, Indonesian rupiah, Korean won, Malaysian ringgit, Philippine peso, Taiwanese dollar and Thai baht; From Europe we have the Czech koruna, Hungarian forint, Polish zloty, Romanian leu, Slovak koruna and Turkish lira. From the Middle-east and Africa we have the Israeli shekel and South-African rand. Since we are interested in currencies in free float, the data period starts from January 1997 and ends at June 2007. This is because the exchange rate systems of the countries above became floating in this period. The exact starting dates per currency are given in *Table 1*.

The exchange rates are expressed as the amount of emerging market currency per US dollar, that is, the price of one US dollar in emerging market currency. Further, the exchange rates correspond to Reuters 07:00 GMT middle rate fixings.

In previous research, different instruments are used for investments in the currency markets. One possibility is to apply trading rules on spot exchange rates, corrected for interest rate differentials (Dooley and Shafer (1976)). The fact that returns need to be corrected is because two currencies are involved, leading to different interest rates received between the long currency and the short currency. Another approach is to use futures or forward prices. These prices already include the interest rate differential (Levich and Thomas (1993)). Previous studies have shown that the interest rate differential is negligible for developed market currencies (Sweeney 1986, LeBaron (1999) and Okunev and White (2003)). For this reason, many studies regarding trading strategies on developed market currencies neglect the interest rate differential. In our case however, we are dealing with emerging market currencies, for which the interest rate differentials might be substantial and thus should not be ignored. This is analyzed in more detail later in this Section.

Another issue to be mentioned is the tradability of the forward markets of currencies. Trading may be restricted by capital controls and foreign exchange convertibility restrictions. In our sample, 12 of the 21 currencies are not freely tradable and are traded as non-deliverable forwards (NDF). An overview of the deliverable/non-deliverable status for all the currencies during our sample period can be found in *Table 1*. NDFs are different from deliverable forward contracts in the way that they are settled in cash and not in the underlying instrument: At maturity, the agreement is settled by taking the difference of the spot exchange rate and the exchange rate agreed beforehand and a net payment is made in convertible currency (often in US dollar) proportional to that difference. Another difference with deliverable forwards is that NDFs trade outside the direct jurisdiction of the authorities of the corresponding currencies. Further, the pricing of NDFs is not constrained by domestic interest rates.

The interest rates available in this dataset are adjusted for the tradability of the currencies. Historical implied interest rates from offshore NDF contracts will be used for return calculations in case of non-deliverable currencies and local rates in case of deliverable currencies. The historical implied interest rates are obtained from an anonymous broker and Bloomberg Interbank interest rates are extracted from Bloomberg. The interest rate series are three-month rates for each currency because on average, the trading strategies hold its positions for roughly 3 months (see Section 3).

Table 1: Deliverable / non-deliverable status of emerging market currencies

Currency	**Code**	**Float**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Taiwan dollar	TWD	dec-96	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
Peruvian sol	PEN	dec-96	N/T	N/T	ND	ND	ND	ND	ND	ND	ND	ND	ND
Indian rupee	INR	dec-96	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
Mexican peso	MXN	dec-96	D	D	D	D	D	D	D	D	D	D	D
S. African rand	ZAR	dec-96	D	D	D	D	D	D	D	D	D	D	D
Czech koruna	CZK	may-97	D	D	D	ND	ND	ND	ND	ND	ND	ND	ND
Israeli shekel	ILS	jun-97	ND	D	D	D	D	D	D	D	D	D	D
Thai baht	THB	jul-97	D	D	D	D	D	D	D	D	D	D	D/ND
Philippine peso	PHP	jul-97	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
Indonesian rupiah	IDR	aug-97	D	D	D	D	ND	ND	ND	ND	ND	ND	ND
Korean won	KRW	dec-97	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
Slovak koruna	SKK	oct-98		D	D	D	D	D	D	D	D	D	D
Brazilian real	BRL	feb-99			ND	ND	ND	ND	ND	ND	ND	ND	ND
Chilean peso	CLP	sep-99			ND	ND	ND	ND	ND	ND	ND	ND	ND
Colombian peso	COP	sep-99			ND	ND	ND	ND	ND	ND	ND	ND	ND
Polish zloty	PLN	apr-00				D	D	D	D	D	D	D	D
Turkish lira	TRY	feb-01					D	D	D	D	D	D	D
Hungarian forint	HUF	may-01					D	D	D	D	D	D	D
Argentine peso	ARS	jan-02						ND	ND	ND	ND	ND	ND
Romanian leu	RON	oct-04								ND	D/ND	D/ND	D/ND
Malysian ringgit	MYR	jul-05									ND	ND	ND

This table is identical to Table 1 in De Zwart et al. (2009). The table indicates for each of the 21 market currencies whether the currency was deliverable (D), non-deliverable (ND) or not tradable (N/T) in the period of 1997 until 2007. The table also contain the date when the currency became floating. Blank cells indicate that the currency was not floating at that time.

Define S_t as the spot rate at time *t*. Then, the (excess) return of a foreign investment can be written as:

$$r_t = s_t - s_{t-1} + i_{t-1}^{US} - i_{t-1}^{EM} \quad , \tag{1}$$

where, s_t is the log spot rate at time *t*, i_{t-1}^{EM} is the interest rate in the emerging market country and i_{t-1}^{US} is the interest rate in the US.

Summary statistics for the daily returns are given in *Table 2*[1]. The first column shows the mean of the annualized daily returns of holding a US dollar the entire period, as in a buy and hold strategy. Recall that the exchange rate is defined as the amount of emerging market currency per dollar. Thus if the emerging market currency has appreciated relative to the US dollar, the amount of emerging market currency for one dollar will decrease which leads to a *negative* sign for the return. In general, we can see that the emerging market currencies have appreciated over our sample period. Only the Taiwanese dollar has depreciated with an average return of -1.63 percent per year. The Indonesian rupiah is the most volatile currency in the sample, with an annualized standard deviation of 25.01 percent per year. The second column contains the annualized interest rate differential for each currency. We can see that the interest rate differential is substantial with respect to the mean returns and therefore cannot be neglected. In case of Turkey and Brazil for example, the mean returns are entirely as a consequence of the differential. Further, the returns are not really skewed but 15 of the 21 currencies shows excess kurtosis compared to a kurtosis of 3 in case of a normal distribution, which indicates that the distributions are fat-tailed and have high peaks. This is confirmed by the Jarque-Bera statistics which rejects normality for most of the currencies.

Table 2: Summary statistics of currency returns

	Mean	**Int.diff.**	**Stdev**	**Skewness**	**kurtosis**	**JB**
TWD	1,63	-0,08	5,55	0,08	8,58	163,54
PEN	-4,08	-2,79	3,43	-0,47	5,37	24,71
INR	-4,91	-6,08	4,34	0,18	8,37	152,08
MXN	-7,03	-9,81	8,26	0,78	5,16	37,28
ZAR	-3,38	-7,29	15,84	0,33	3,97	7,28
CZK	-6,01	-0,96	11,48	-0,16	2,71	0,90
ILS	-1,43	-3,44	7,47	1,50	8,53	187,81
THB	-6,70	-2,22	10,70	-3,04	21,52	1787,50
PHP	-7,02	-7,68	7,99	-0,45	6,84	73,09
IDR	-11,94	-12,77	25,01	-0,26	10,36	254,28
KRW	-6,27	-2,03	9,55	-0,23	7,52	92,82
SKK	-9,24	-2,79	10,19	-0,16	2,59	1,12
BRL	-12,14	-12,30	17,90	1,71	10,92	291,71
CLP	-0,62	-1,34	9,15	-0,06	2,63	0,54
COP	-5,11	-5,23	9,21	0,10	6,04	33,56
PLN	-12,38	-4,77	10,88	0,17	2,63	0,83
TRY	-27,39	-26,64	16,50	0,51	5,28	18,16
HUF	-13,49	-5,66	12,07	0,65	4,12	8,23
ARS	-12,28	-8,56	8,18	-1,16	4,59	19,50
RON	-10,43	-2,40	8,67	0,17	1,99	1,24
MYR	-4,17	1,63	3,52	0,31	2,66	0,35

The table reports the summary statistics of the 21 market currencies, measured in annualized percentage points of daily returns for the sample period starting from the point they where floating until 2007. The statistics are based on holding a long position in the US dollar and a short position in the emerging market currency.

[1] The results are somewhat different than in De Zwart et al. (2009). This is because they report annualized monthly returns. We see for example that the kurtosis in our case is higher, which is in line with the stylized fact that returns at higher frequency have higher kurtosis.

2.2 Foreign exchange reserves

Foreign exchange reserves are deposits of a foreign currency held by a central bank. These reserves have the purpose to keep the local currency stable when, for example, economic shocks occur. For the analysis with foreign exchange reserves as a proxy for intervention in Section 4.1, we have available the reserves position for each currency at the end of each month of our sample period, measured in US dollar. The data is extracted from websites of central banks and *International Financial Statistics*. For most of the countries, reserves data are made available directly after a month. For several countries, the data is published on weekly or even daily basis.

We should not disregard the composition of the reserves in terms of currencies. This is because the reserves are measured in US dollar, but contain other reserve currencies as well. Thus a positive change in reserves may be due the fact that the dollar has become more worth relative to other another currency instead of central bank (intervention) operations. *Table 3* shows the composition of the reserve currencies for emerging markets in general. We see that larger parts, about 60-70% of the reserve currencies are US dollars. However, the proportion of US dollars is declining over the years as the proportion of Euros is increasing[2].

Table 3: currency decomposition of foreign exchange reserves

currency	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
US dollar	74.33	73.67	72.69	73.32	72.49	66.61	61.86	62.03	62.10	61.04	61.65
pounds sterling	2.24	2.21	2.47	2.54	2.68	2.67	3.65	4.78	4.98	5.89	5.83
Deutsche mark	13.86	13.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
French francs	2.07	2.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Japanese yen	4.64	4.35	3.96	2.70	2.35	2.19	1.58	1.68	1.70	1.31	1.76
Swiss francs	0.59	0.55	0.48	0.21	0.21	0.13	0.12	0.14	0.07	0.08	0.08
Netherlands guilder	0.33	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ECUs	0.11	0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
euros	0.00	0.00	19.00	19.73	21.25	26.94	31.08	30.02	29.72	30.11	29.16
other	1.83	2.62	1.41	1.50	1.02	1.46	1.70	1.35	1.43	1.58	1.51

This table reports the decomposition of foreign exchange reserves of emerging markets, from 1997 until 2007. *Source: IMF*

To check how the change in reserves behaves relative to the EUR/USD spot rate we compute the correlation coefficients between the change in log reserves and the EUR/USD rate. A positive correlation coefficient indicates that a positive change in reserves is associated with an appreciating US dollar. In *Table 4*, we generally see that due to the low values, changes in the reserves are not because of the

[2] Note that in the present, the US dollar as a reserve currency has been under a great pressure due to the economic crisis. The reason is that the US government has injected substantial amounts of dollars in the economy which leads to inflation risk and depreciation of the dollar.

EUR/USD rate. For a graphical illustration, we also plot the change in reserves against the EUR/USD rate for several countries in *Appendix A1*.

Table 4: correlation between the changes in reserves and the EUR/USD rate.

TWD	ZAR	CZK	PEN	INR	MXN	ILS	THB	PHP	IDR	KRW
0.086	-0.222	0.192	-0.260	0.011	0.045	0.003	-0.136	-0.145	-0.110	-0.010
SKK	**BRL**	**CLP**	**COP**	**PLN**	**TRY**	**HUF**	**ARS**	**RON**	**MYR**	
0.041	-0.192	-0.006	-0.096	-0.107	0.101	-0.041	-0.119	0.266	-0.258	

This table reports correlation between changes in the log reserves and the EUR/USD rate for each country over their corresponding sample periods.

2.3 Foreign exchange intervention data

Foreign exchange intervention comprises the purchases and sales of a currency by a central bank. While intervention data for developed markets are more and more available, the availability of intervention data for emerging markets is still scarce. For example, intervention data for the Asian countries in IMF (2007) are confidential. Moreover, there are some countries for which the intervention data is available only at monthly basis, whereas we are more interested in intervention data on daily basis. Nevertheless, we have daily intervention series available for Peru, provided by the central bank of Peru (BCR), and for Turkey, which is publically available on their central bank (CBRT) website. These series represents the amount of US dollar the central banks have bought or sold.

In case of Peru, one of the motives for intervention is to reduce excess volatility by leaning against the wind. The interventions are not pre-announced, but made available at the end of the day when they take place. It is known that the media emphasizes the amount of intervention when the BCR intervenes, which indicates the ‘degree’ of smoothing of the path of the exchange rate. In case of Turkey on the other hand, the CBRT has stated that it lets the market conditions determine the exchange rate, thus keeping the number of interventions limited. However, the central bank can intervene in case of excess volatility. Further, it is known the CBRT intervenes discretionary[3].

Figure 1 shows the PEN/USD and TRY/USD exchange rates, together with the amount of US dollars bought or sold by the BCR and CBRT during our sample period. We see that in case of Peru, the frequency and size of intervention of BCR has increased throughout our sample period. In our sample period, the BCR is a net buyer of US dollars and in particular, the BCR has bought heavily during the end of our sample period. With the bare eye, we can see that the exchange rate seems to be smoother in periods where the BCR has persistently intervened than in other periods. Further, we see that in those

[3] For more information of intervention policy of Peru and Turkey, we refer to BIS (2005).

periods a decrease in the PEN/USD exchange rate is accompanied with purchases of dollars, which indicates leaning against the wind behavior. On the other hand, it is clear that the CBRT has scarcely intervened in our sample period, which is in line with their policy. The CBRT is also a net buyer of US dollars.

Table 5 provides summary statistics for the intervention series. The average amount of intervention is positive for both countries denoted by Mean (I_t), which confirms that both countries are net buyers throughout the sample. Also, the average absolute size is given. the average intervention size of the BCR is around 21 million, which is around 10% of the average daily market turnover and that the CBRT, with an average size of exceeding one billion US dollar, around 50% of the average daily market turnover during the sample period[4]. Thus, the CBRT intervenes scarcely, but with large amounts. Further, the table contains conditional probabilities of intervention. This gives some indication of the clustering of intervention. p($I_t \neq 0 | I_{t-1} = 0$) stands for the probability of intervention given that there was no intervention in the previous period and p($I_t \neq 0 | I_{t-1} \neq 0$) stands for the probability of intervention given that there was intervention in the previous period. In particular, the intervention of Peru seems to be very persistent with p($I_t \neq 0 | I_{t-1} \neq 0$) equal to 0.815. Finally, the table also reports the correlation between the *monthly* intervention data with the changes in foreign exchange reserves. This is further addressed in Section 4.1.

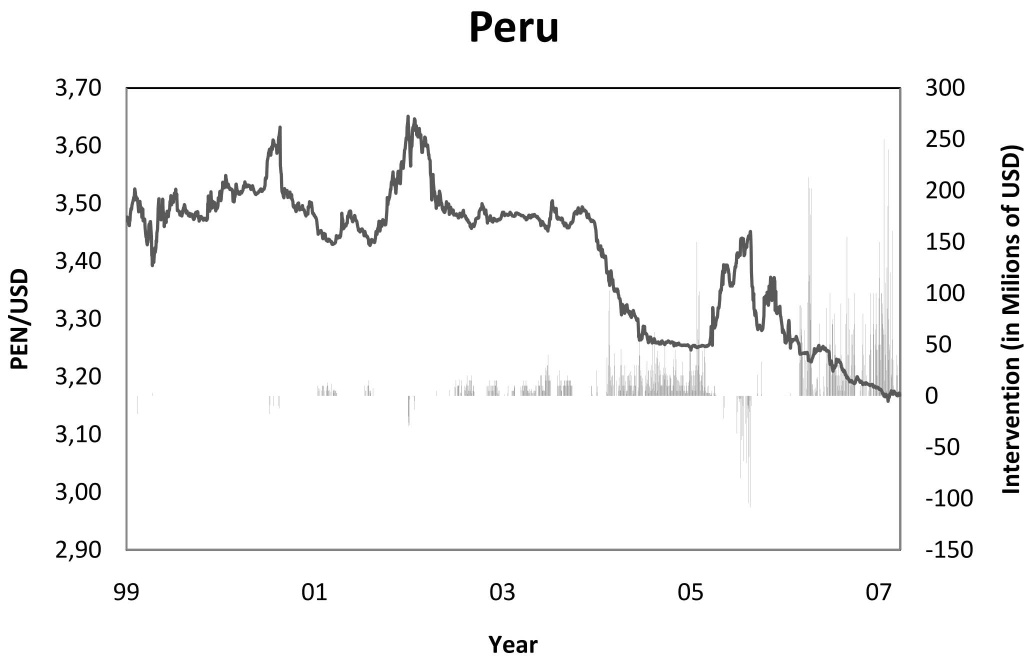
Table 5 summary statistics intervention data

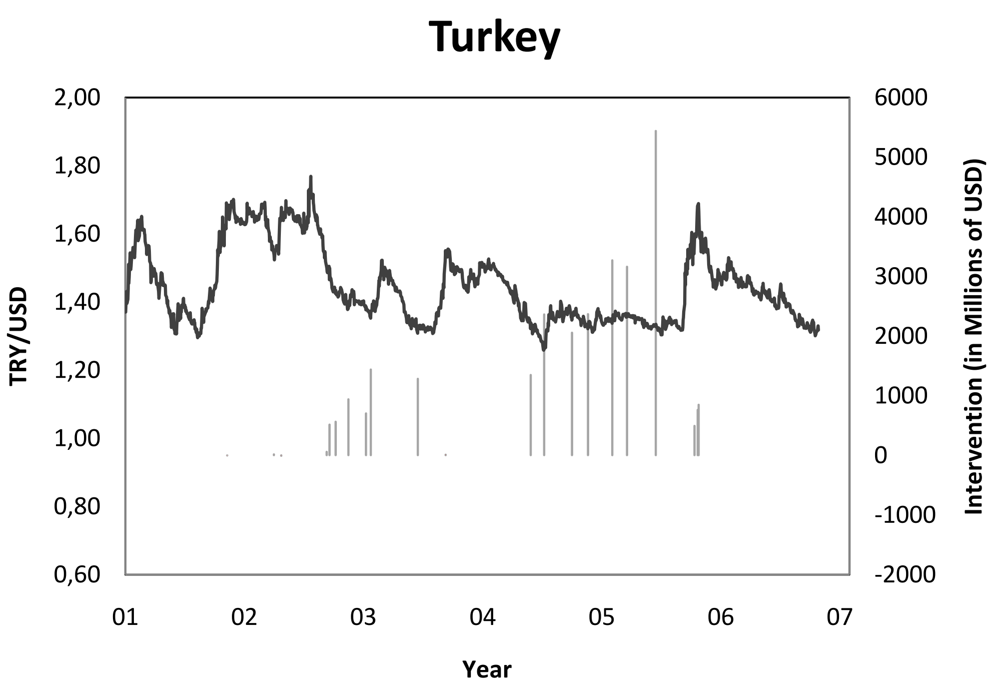
	Peru	**Turkey**
Mean (I_t)	21.6	1114.7
Mean ($\|I_t\| \mid I_t \neq 0$)	24.4	1216.9
p($I_t \neq 0$)	0.351	0.014
p($I_t \neq 0 \| I_{t-1} = 0$)	0.099	0.013
p($I_t \neq 0 \| I_{t-1} \neq 0$)	0.815	0.048
Corr(*I.Res*)	0.613	0.543

I_t equals the intervention at time t in millions of dollars. The final row gives the correlation between the actual *monthly* intervention and changes in foreign exchange reserves.

[4] The numbers used here for average daily turnover are rather rough estimates. Daily average turnover data can be obtained from surveys of BIS, which is available on their website at three-year frequency.

Figure 1: Exchange rate and intervention over time





This figure contains the PEN/USD and TRY/USD and the amount of intervention of the BCR (upper panel) and BCRT (lower panel), from the period of since the currencies were floating, until June 2007

2.4 Macroeconomic variables

For the simultaneity problem we address in Section 4.2, we have several macroeconomic variables available that may influence the exchange rate. *Table 6* shows the variables we consider and their expected influence on the exchange rate. All the variables are obtained from *International Financial Statistics* on a monthly frequency except for GDP, which is only available at quarterly frequency.

Table 6: macroeconomic variables

Variable	Influence
WPI (Wholesale Price Index)	This index represents the price level of a basket of wholesale goods. If the WPI rise, this indicates for inflation and the exchange rate is expected to weaken.
CPI (Consumer Price Index)	This index represents the average price of consumer goods and services purchased by households. If the CPI rises, this indicates inflation and the exchange rate will weaken.
Import prices	Countries need the foreign currency for their imports, which strengthens the foreign currency and weakens the domestic currency.
Export prices	The same holds for exports, but the other way around.
Broad money supply	Broad money supply is defined as the widest measurement of money supply. An increase in money supply could cause inflation which in turn causes the exchange rate to decline.
GDP[5]	The GDP indicates economic growth. If the GDP rises, this leads to more attractive investment opportunities. This in turn increases the demand for domestic currency and therefore we expect the currency to appreciate.

This table contains the macroeconomic variables which we use at a later stage. The variables are obtained from *International Financial Statistics* for each of the 21 emerging market countries, for the period 1997-2007. The variables are on monthly frequency, except for the GDP, which is available at a quarterly frequency.

[5] The GDP series we have available are growth rates. This is not a problem as it is discussed in Section 5.1, we use growth rates of each variable.

3 Trading rule profits

In this section we investigate the profitability of technical trading rules for each of the 21 currencies discussed in Section 2.1.

Technical analysis is the discipline which attempts to predict future price movements based on patterns in historical prices. Technical analysis often makes use of graphs. Because interpreting charts can be subjective, many technical trading rules have been developed in practice. Trading rules indentify moments to buy or sell an asset, by detecting patterns in the historical prices. In this research, we consider different types of rules that are extensively used, namely the Moving Average rule and the Support and Resistance rule. The reason that we consider two different types of trading rules is that we also want to test if the relationship of trading rule profits with central bank intervention varies between rules.

3.1 Methodology

The first technical trading rule we consider is the Moving Average rule, which is the most widely used rule in practice. The idea behind moving averages is that they smooth (volatile) series. The simple form of this rule makes use of a fast moving average and a slow moving average. When the fast moving average crosses the slow moving average, a trend is considered to be initiated. More specifically, the Moving Average rule returns a buy signal for a particular currency (in our case the US dollar) if the fast moving average based on *H* days is above the slow moving average based on *L* days and a sell signal vice versa. Thus, the rule returns a buy (sell) signal for the US dollar when the emerging market currency is depreciating (appreciating). Define $MA_t(H,L)$, a buy or sell signal, as :

$$MA_t(H,L) = \begin{cases} 1, & \frac{1}{H}\sum_{h=1}^{H} S_{t-h} \geq \frac{1}{L}\sum_{l=1}^{L} S_{t-l} \\ -1, & otherwise \end{cases} , \quad (2)$$

where $H < L$, and S_t is the exchange rate in EM/$ for day *t.*

In the existing literature, the most trivial variant of the rule (where *H* is set equal to 1) is sometimes used in order to avoid data mining biases by searching the entire space for *H* and *L,* see for example LeBaron (1999) and Saacke (2002). De Zwart et al. (2009) however, consider the combined signal for a range of *H* and *L* instead of relying on one single choice of these moving average lengths. This is to prevent conclusions based on one specific parameter setting. Further, moving average rules are sometimes modified with bands. The bands are introduced to prevent the signal changes too often (high turnover) when the slow and fast moving average are close together.

We decide to select the same ranges as in De Zwart et al. (2009) for slow and fast moving average as we are working with the same dataset. For the fast moving average rules they select all the rules between 5 and 20 days and for the slow moving average rule they select all the rules between 25 and 65 days, resulting in 144 moving average rules that are applied. Still, in order to reduce the data mining bias, the results are based on the average of those rules instead by relying on the best performing rule. Bands are not considered in this analysis as previous studies, like LeBaron (1999) and De Zwart et al. (2009), have shown that the turnover is relatively low for simple moving averages.

The second rule we consider is the Support and Resistance rule. The idea behind this rule is that prices of securities tend to stop and reverse at 'support' and 'resistance' levels. A Support is a minimum price of a certain history at which buyers attempt to prevent the price from dropping further. Similarly, a resistance is where sellers attempt to prevent the price to go higher. According to the rule, the price will continue to drop (rise) once a support (resistance) is broken. The Support and Resistance rule is also known as "Channel rule" or "Trading range breakout". More specifically, the Support and Resistance rule returns a buy (sell) signal for the US dollar if the spot exchange rate on day *t* is above (below) the maximum (minimum) of the pre-specified past number of days. Define $SR_t(N)$, as the buy or sell signal, as:

$$SR_t(N) \begin{cases} 1 & if\ S_t > \max\left(S_{t-1,\dots,}S_{t-N}\right), \\ -1 & if\ S_t < \min(S_{t-1,\dots,}S_{t-N}), \\ SR_{t-1}(N) & \text{otherwise}. \end{cases} \quad (3)$$

Our variant is similar to the channel rule introduced by Donchian (1960), which is also referred to as the "Donichan channel system". Sullivan et al. (1999) provide another variant for this rule where they hold the position for a pre-specified number of days. However, this variant has much higher turnover than our variant.

Again, we combine a range of Support and Resistance rules for different values of *N*. We apply the same range of rules as in De Zwart et al. (2009), that is we vary *N* between 25 and 65 days. The rules are selected out of a wide range where *N* is varied between 5 and 200 in steps of 5 days and selection is based on turnover levels per year and Sharpe ratios. Similar to the Moving Average rules, we take the average of the range to analyze the performance of the Support and Resistance rules.

In addition, we also consider a strategy that is a combination of Moving Average and Support and Resistance rules to assess the overall performance of the technical trading rules over the emerging markets. We define the signal of the combined strategy basically as the average of two trading rule signals above:

$$C_t = (MA_t + SR_t)/2 \quad , \quad (4)$$

where C_t is +1 (-1) if on average the emerging market currency is depreciating (appreciating). For this particular strategy, we employ a volatility weighted portfolio over the currencies. The general idea behind a volatility weighted portfolio is that each currency adds about the same amount of risk to the portfolio risk. Because volatility is usually time-varying, we choose to weight each daily return by the inverse of the *ex post* volatility over the past year[6].

In order to calculate the returns from the strategies, the trading signal indicators need to be multiplied with the actual returns of the exchange rate:

$$x_t^z = Z_t \, r_t \tag{5}$$

where x_t is the dynamic return on a particular trading strategy and r_t is the return on the currency defined as in (4) and Z_t is the trading rule signal at day *t*. Note that the strategies are self-financing because if we go long in one currency, we automatically go short in the other currency and vice versa. In our case, we go long (short) in the US dollar and at the same time short (long) in the emerging market currency if a buy (sell) signal occurs. The positions are held until the rule gives the opposite signal.

The return of the 'weighted combination strategy' is defined as follows:

$$x_t^{C,VW} = \frac{1}{\sum_{i \in Q_t} \frac{1}{\sigma_{i,t}}} \sum_{i \in Q_t} \frac{1}{\sigma_{i,t}} \, x_t^C \tag{6}$$

Where $x_t^{C,VW}$ is the volatility weighted return on day *t*, Q_t is the set of currencies at day *t* and $\sigma_{i,t}$ is the volatility of exchange rate over the previous 262 days for country *i*.

To assess the significance of the returns we implement a bootstrap approach. Several ways to implement this approach have been introduced in the literature; see Levich and Thomas (1993) or LeBaron (1999). We follow the procedure of LeBaron (1999): A bootstrapped random walk series is created by random resampling (with replacement) the log price differences of the original series. These are added to the first price of the series which is constrained. This procedure is repeated 1000 times. For each of the series, we apply the technical trading strategies as described above and calculate the returns. Finally, the dynamic returns on the original series will be compared with the dynamic returns on the 1000 bootstrapped series. Hence, we create an empirical distribution of the returns. In this case, *p*-value is the fraction of the bootstrapped series that leads to higher returns than the original series. The intuition is that if the original series lead to higher returns than the bootstrapped series, then we can say that the original series contain information and patterns that can be detected by technical trading rules. Whereas the *t*-statistic assumes normality and independently and identically distributed returns, the bootstrapped *p*-value does not rely on any distributional properties.

[6] We define that one year consists of 262 (trading) days. For returns of the first 262 days, we consider the volatility over the first year. In that way, we do not lose one year of observations.

The bootstrapped *p*-value is used to evaluate the statistical significance of the dynamic returns, where we choose a significance level of 10%. Since we are working with excess returns, we also consider the Sharpe ratio in order to evaluate the economical significance of the returns.

3.2 Empirical results

The statistics for the dynamic returns of the trading strategies are given in *Table 7.* The table contains the annualized daily mean, standard deviation and Sharpe ratio, the bootstrapped *p*-value and the average number of trades per year.

We can see that for the Moving Average strategies, 20 of the 21 currencies have positive returns. The only currency with a significant negative return is the Mexican Peso. In case of Support and Resistance, Poland has negative returns as well, but not significant. The Indonesian rupiah has the most volatile trading rule profits for both types of rules. Based on the bootstrapped *p*-value, we see that the Moving Average strategies yield better performance than the Support and Resistance strategies with 11 versus 4 significantly positive returns. The findings are in line with the results of different Moving Average rules and Momentum rules reported in Pukthuanthong-Le and Thomas (2008). In terms of risk adjusted returns, the Taiwanese dollar and the Colombian peso have the highest Sharpe ratio which is above 1. Again, the Moving average strategy is outperforming the Support and Resistance strategy as for 18 of the 21 currencies the Sharpe ratio is higher for the former.

The weighted combination strategy has good performance with a mean return of 3.82 per cent per year. We see that individual currencies with the highest average returns also have the highest volatilities. These currencies obtain the lowest weights, which also explain the lower mean return of the weighted strategy. However, the decline of the average return is more than compensated by the reduction of risk, which is reflected in a Sharpe ratio of 1.44. Further, we see that the mean return is statistically significant with a bootstrapped *p*-value of 0.00. Hence, diversification across countries does make sense in this case.

We also see in *Table 7* that there are a relatively small number of trades. A trade occurs when the sign of the trading signal changes. For Moving Average strategies, between 6 and 7 trades occur per year, while for the Support and Resistance strategies this is between 3 and 4 trades per year. On average, this equals 5.17 trades per year, or a holding period of around two and a half months. These numbers are more or less the same for trading strategies on developed markets in LeBaron (1999). In the calculation of the returns, transaction costs have not been taken into account. Note that for a trade, transaction costs need to be taken in to account twice, because if we buy one currency, we automatically sell the other currency. Not much research has been done regarding the size of transaction costs when trading in emerging markets. Bonser-Neal et al. (1999) investigate transaction costs in Indonesia and conclude that it does not differ much from developed markets. De Zwart et al.

(2009) investigate what influence transaction costs have on the trading rule profits and find that for most countries the Moving Average and Support and Resistance strategies have break-even transaction costs exceeding 0.4 percent. This is still above the level of transaction costs encountered by a large institutional investor. Further, transaction costs most likely vary over the countries. Because we are working with 21 countries, we decide not to take transactions costs into account for the rest of this research.

Altogether, we confirm earlier studies and we conclude that technical trading rules seem to be profitable for emerging market currencies.

Table 7: Performance of technical trading rules

MA returns	Mean	Stdev	Sharpe	p- value	#Trades
TWD	4.93	4.10	1.20	0.00***	5.69
PEN	1.85	3.07	0.60	0.20	6.56
INR	2.65	3.88	0.68	0.21	5.58
MXN	-3.90	8.90	-0.44	0.97	8.34
ZAR	6.39	14.15	0.45	0.10*	6.81
CZK	1.01	10.93	0.09	0.44	7.84
ILS	5.02	6.20	0.81	0.01***	6.47
THB	6.39	7.79	0.82	0.03**	6.51
PHP	3.83	8.17	0.47	0.15	5.96
IDR	14.80	20.74	0.71	0.03**	6.92
KRW	4.74	7.05	0.67	0.03**	7.33
SKK	3.61	9.91	0.36	0.22	7.29
BRL	11.52	14.95	0.77	0.02**	6.45
CLP	5.69	7.85	0.72	0.02**	6.47
COP	10.14	7.57	1.34	0.00***	5.75
PLN	3.68	9.64	0.38	0.31	7.32
TRY	10.68	13.93	0.77	0.22	7.22
HUF	1.35	10.68	0.13	0.52	8.53
ARS	3.12	8.06	0.39	0.65	7.10
RON	9.13	8.59	1.06	0.09*	6.07
MYR	1.91	3.34	0.57	0.57	6.50

SR returns	Mean	Stdev	Sharpe	p- value	#Trades
TWD	4.45	4.12	1.08	0.00*	3.02
PEN	1.18	3.00	0.39	0.45	3.18
INR	2.26	3.95	0.57	0.39	2.54
MXN	-4.54	9.25	-0.49	0.98	4.25
ZAR	1.42	14.13	0.10	0.42	3.87
CZK	2.47	11.10	0.22	0.36	3.85
ILS	1.47	6.20	0.24	0.30	4.01
THB	3.40	8.06	0.42	0.24	3.03
PHP	1.19	8.41	0.14	0.55	2.91
IDR	10.53	21.41	0.49	0.12	3.42
KRW	2.10	7.05	0.30	0.24	3.78
SKK	3.22	10.22	0.31	0.30	3.63
BRL	10.21	15.40	0.66	0.04**	3.33
CLP	4.20	7.85	0.53	0.08*	3.53
COP	7.14	7.53	0.95	0.00***	3.18
PLN	-2.14	10.15	-0.21	0.85	4.51
TRY	8.60	14.21	0.61	0.30	3.61
HUF	1.90	10.79	0.18	0.49	3.79
ARS	0.05	8.21	0.01	0.74	3.92
RON	6.18	8.45	0.73	0.31	3.83
MYR	2.70	3.26	0.83	0.56	3.29
Vol.W.	3.82	2.65	1.44	0.00***	6.12

The table reports the annualized daily return (in percentage points) , the standard deviation, Sharpe ratio, bootstrapped *p*-value and the average number of trade per year of Moving Average and Support and Resistance strategies for 21 emerging market currencies from six months after they became floating until June 2007. The table also contains the volatility weighted combined strategy. *, ** and*** indicate for significance at 10%, 5% and 1% respectively.

4 Trading rule profits and central bank intervention

In Section 3.2, we report that technical trading rules are profitable for emerging market currencies. In this section we investigate if there is a relationship between those profits and central bank intervention. We use a foreign exchange reserves proxy for intervention, and we follow the procedure of Szakmary and Mathur (1997) by performing regression tests of trading rule returns on changes in reserves.

4.1 Regression tests using changes in reserves as a proxy for intervention

4.1.1 Methodology

Because of the limited availability of actual intervention data, we use changes in foreign exchange reserves as a proxy for central bank intervention similar to Szakmary and Mathur (1997). One question that arises is the usefulness of foreign exchange reserves as a proxy because it can contain non-intervention activities, such as a government payment of debt in foreign currency or swap agreements between central banks and commercial banks, and intervention can be deliberately hidden and therefore not show up in reserves. Further, as discussed in Section 2, changes in other exchange rates like the EUR/USD may influence the value of reserves. Several studies have been conducted to examine this issue. Neely (2000) does not find strong correlation between intervention and changes in foreign exchange reserves, ranging from 0.1 to 0.4, for several developed currencies. However, according to IMF (2007), the correlations of the change of reserves and intervention for several Asian emerging markets are between 0.8 and 0.9. For Peru and Turkey, we find reasonable correlation coefficients of 0.613 and 0.543 respectively (see *Table 5* in Section 2.3).

As mentioned above, we follow the procedure of Szakmary and Mathur (1997). If a central bank intervenes by buying (selling) an amount of a particular foreign currency, the reserves should increase (decrease). Define intervention as:

$$IV_{j,t} = abs\,[\log(Res_{j,t}) - \log(Res_{j,t-1})] \quad , \qquad (7)$$

where $IV_{j,t}$ is intervention by a central bank of country *j* during month *t* and $Res_{j,t}$ is the foreign exchange reserves of bank *j* at the end of month *t*. In words, intervention is defined as the absolute change of the log reserves between two consecutive months.

Intervention can be profitable if central banks 'lean against the wind'. That is, central banks slow down the change of the exchange rate by going in to the opposite direction of investors. For example, if investors are selling currency in a period, then the central bank is likely to buy the currency in the next period. Intervention of this kind can occur if the exchange rate moves to fast from equilibrium, but also if the exchange rate moves towards the equilibrium. Slowing down movements can generate trends in the exchange rate, which can be picked up by technical trading rules.

Define ‘Leaning against the wind’ intervention as:

$$IVL_{j,t} = \begin{cases} IV_{j,t} & \text{if } \left(S_{j,t} - S_{j,t-1} > 0 \ \text{ and } Res_{j,t} - Res_{j,t-1} < 0\right) \\ IV_{j,t} & \text{if } \left(S_{j,t} - S_{j,t-1} < 0 \ \text{ and } Res_{j,t} - Res_{j,t-1} > 0\right) \\ 0 & \text{otherwise} \end{cases} \quad , \qquad (8)$$

where $IVL_{j,t}$ states that intervention is leaning against the wind for country j during month t and $S_{j,t}$, is the spot exchange rate on the last day of month t[7]. In words, leaning against the wind is defined as the appreciation (depreciation) of the emerging market currency that is accompanied by an (decrease) increase in the US dollar reserves in a particular month. Not all intervention is leaning against the wind; we summarize all the other types of intervention into a single non-leaning against the wind variable, which is defined as follows:

$$IVN_{j,t} = IV_{j,t} - IVL_{j,t} \quad , \qquad (9)$$

Where $IVN_{j,t}$ states that intervention is not leaning against the wind for country j during month t.

Due to the fact that the foreign reserves are available only at monthly frequency, the trading rule returns obtained in the previous section are aggregated to monthly bases.

With the variables defined above, we perform the following regressions for each currency:

$$R_{j,t} = b_{j,0} + b_{j,1} IVL_{j,t} + b_{j,2} IVN_{j,t} + e_{j,t} \quad , \qquad (10)$$

$$R_{j,t} = b_{j,0} + b_{j,1} IVL_{j,t} + e_{j,t} \quad , \qquad (11)$$

where $R_{j,t}$ is the monthly return for currency j over month t, $b_{j,0}$ the constant and $e_{j,t}$ is the error term. The constant term $b_{j,0}$ can be interpreted as the mean return unexplained by IVL_t and IVN_t.

We expect regression (10) and (11) only to explain a small part of the variation in the returns. First, because we are working with data on monthly basis, we cannot detect activities within a month; the level of reserves may fluctuate substantially if the central bank heavily buys and sells an equal amount of dollars in a month, but the net change in reserves at the end of that particular month is rather small. Second, as discussed at the beginning of the section, changes in reserves may be an imperfect proxy for central bank intervention. Further, because we are working with monthly data, the

[7] Note that the signs are different than in Szakmary and Mathur (1997). This is because they express the exchange rate as the amount of US dollars per foreign currency.

number of observations is relatively small, ranging from 125 observations at most to only 16 observations for the Malaysian ringgit[8]. Because of the relatively small sample size, the regression coefficients will be evaluated on their sign and a significance level of 1%, 5% and also 10% using *t*-statistics.

Regardless of the above, regression (10) and (11) can be interpreted as follows. In this setting, we assume that the relationship between leaning against the wind intervention and trading rule returns is linear. If leaning against the wind help explain the positive trading returns, we expect $b_{j,1}$ to be significantly positive. At the same time, we expect that non-leaning against the wind operations do not or negatively contribute to trading rule profits. That is, $b_{j,2}$ should be insignificant or significantly negative. If $b_{j,0}$ is insignificant as well, we can conclude that the proxy for leaning against the wind intervention can fully explain the profitability of technical trading rules. Hence, the ideal situation would be that $b_{j,1}$ is positive, $b_{j,2}$ is insignificant or negative and $b_{j,0}$ to be insignificant. In this case, in absence of leaning against the wind intervention, the trading rule profits would be non-positive. If we expect that $b_{j,2}$ is insignificant, we can delete the redundant IVN_t variable in order to improve the efficiency of the estimates of $b_{j,1}$, which leads to regression (14).

In addition to the procedure of Szakmary and Mathur (1997), we conduct several more tests which can be considered as sensitivity analyses. In the first analysis we allow for separate intercepts for $b_{j,1}$ and $b_{j,2}$ by introducing dummy variables. In this setting we investigate if there is a difference in the mean return unexplained by our two variables on leaning against the wind intervention months and on non-leaning against the wind intervention months. The regression is defined as follows:

$$R_{j,t} = c_{j,1}D_{1,t} + c_{j,2}D_{2,t} + b_{j,1}IVL_{j,t} + b_{j,2}IVN_{j,t} + e_{j,t} \quad , \tag{12}$$

where $D_{1,t} = 1$ ($D_{2,t} = 0$) if *t* is at a leaning against the wind month and $D_{1,t} = 0$ ($D_{2,t} = 1$) otherwise.

Because of the short sample period for most of the countries, we also perform regression (10) with the returns of the volatility weighted portfolio. Here, we weight the IVL_t and IVN_t variables across the countries in the same way as for the returns.

Also, we aggregate all data and perform a panel regression with fixed effects to still have sensible use of all the data. In this model it is assumed that the marginal effects of leaning against the wind and non-leaning against the wind are the same across all the countries. The constant terms are allowed to vary among countries. Thus, the country specific characteristics that are constant over time will be absorbed in the constant terms. The panel regression is defined as follows:

$$R_{j,t} = \sum_{i=1}^{M} c_i D_{j,t}(i) + \gamma_1 IVL_{j,t} + \gamma_2 IVN_{j,t} + e_{j,t} \quad , \tag{13}$$

[8] For comparison, the sample period in Szakmary and Mathur (1997) varies from 155 to 162 monthly observations.

where $D_{j,t}(i)$ is a unit dummy for country i at month t, and $D_{j,t}(i) = 1$ if $j = i$ and $D_{j,t}(i) = 0$ if $j \neq i$. We expect γ_1 to be significantly positive, γ_2 insignificant or significantly negative, and the c_i insignificant for all countries.

To correct for (possible) heteroskedasticity and serial correlation in the error terms, we use Newey-West standard errors in the estimation of regressions (10), (11) and (12). For the panel regression (13), we have to deal with two issues. The first is that there might also be cross correlation effects between countries. The second is that we have an unbalanced panel, that is, the number of observations differs across countries. We account for these problems with the Driscoll-Kraay covariance estimator, see Driscoll and Kraay (1998) and Hoechle (2007). In short, they apply a Newey-West type of correction to the cross sectional average of the moment conditions in order to obtain standard errors that are consistent and independent over the cross section. Their results suggest that this covariance matrix estimator performs better than alternatives like in SUR (Seemingly Unrelated Regression).

All the regressions discussed in this section will be performed on profits of both Moving Average and Support and Resistance rules. At first glance it may seem that since the moving average rules have higher returns than support and resistance rules, a stronger relation would be found for the moving average rules. This however is not necessarily the case as, for example, all the highly positive returns can occur on non-leaning against the wind intervention months. Thus, it is worthwhile to see if there are different results for different types of trading rules.

4.1.2 Empirical results

The results of regression (10) and (11) are reported in *Table 8* and *Table 9.* First, we discuss the results for the Moving Average strategies. For 8 currencies, we find $b_{j,1}$ to be significantly positive in regression (10). For regression (11) we find significance for 10 currencies. And except for the Hungarian forint and the Argentine peso, $b_{j,2}$ is insignificant or negative for all the currencies. As expected, we can see that the R^2 are generally low, ranging from 0.45% from Brazilian real to 24.64% for the Malaysian ringgit. The R^2 are comparable of those reported in Szakmary and Mathur (1997) for developed countries.

The strongest results are found for the following five currencies: the Indian Rupee, South African rand, Thai baht, Korean Won and the Malaysian ringgit. For those five countries we find $b_{j,1}$ to be significantly positive, $b_{j,2}$ is insignificant or significantly negative and $b_{j,0}$ to be insignificant. Also worth mentioning is the Slovak koruna, which shows a similar relationship, but $b_{j,1}$ is just outside the 10% level. The results imply that the trading rule profits of these currencies may be explained by intervention. This suggests that if there is no leaning against the wind intervention, the trading rule returns do not significantly differ from zero. For the Indian rupee, non leaning against the wind intervention reduces trading rule profits.

For the Taiwanese dollar and the Czech koruna we find a less strong result. That is, the $b_{j,1}$ are significant positive, $b_{j,2}$ is insignificant or significantly negative, but the constant terms are significant for those two currencies. This implies that although leaning against the wind intervention produces trading rule profits, other factors than central bank intervention influence the trading rules profits as well. For the Czech koruna this happens in a negative way. The losses however are not enough to offset the profits gained from intervention, as we found the mean profits to be positive.

For the Mexican peso and the Slovak koruna, we see that $b_{j,1}$ is significantly positive in regression (11), but not in regression (10). Further, we see that for the koruna, $b_{j,2}$ is not significant. By dropping the IVN_t variable as in regression (11), the (direct) effect of $b_{j,1}$ might be more accurately estimated because resulting bias is more than compensated by the gain in efficiency, which for these currencies leads to significant estimates of $b_{j,1}$ in regression (10).

In case of Support and Resistance strategies, we find 6 positively significant $b_{j,1}$ coefficients in regression (10) and 7 in regression (11). Again, except for the Hungarian forint and the Argentine peso, $b_{j,2}$ is insignificant or negative for all the currencies. Although the results for the South-African rand, the Philippine peso and the Slovak koruna are not significant, they are in the right direction. In terms of significance, we generally find similar but weaker results across the currencies compared to the Moving Average strategies. This suggests that the Moving Average rules are better in detecting patterns in the exchange rate movements when central bank intervenes than the Support and Resistance rules.

In *Table 10* we report the results of regression (12). For the Moving Average strategies, we find that for 7 currencies, the $b_{j,1}$ is significant at months of leaning against the wind intervention. The currencies are for which $b_{j,1}$ is significant are comparable of those in *Table 8*. And for those cases, our IVL_t variable can fully account for the profits now as the $c_{j,1}$ are insignificant. On the other hand, the corresponding $c_{j,2}$ terms are sometimes significant. Hence, there are still returns which cannot be explained on non-leaning against the wind intervention months. Again, the results are weaker for Support and Resistance strategies.

Strong results for $b_{j,1}$ are found for the volatility weighted portfolio, in *Table 11*. The *t*-value is 3.413, which is significant at 1% level. Thus for the emerging markets generally, leaning against the wind does contribute to trading rule profits. Non-leaning against the wind intervention seems to reduce profits. Moreover, leaning against the wind intervention can fully account for the profits in this case as well, as $b_{j,0}$ is insignificant.

Table 11 also contains the results of the panel regression. We can see that in for both Moving Average and Support and Resistance strategies, γ_1 is significantly positive and γ_2 is significantly negative. For a small number of countries, the constant term is significant. However, the R^2 of the regressions are relatively low with only 1.94% for Support and Resistance strategies and 2.92% for Moving Average strategies. This indicates that the cross section variation among the countries cannot be captured by a single coefficient. The variation of the $b_{j,1}$ and the $b_{j,2}$ coefficients over the countries in earlier tables are in line with this result.

To summarize, we find evidence for a significant relationship between leaning against the wind and trading rule. Loosely speaking, we roughly expect to find a significant relationship in 2 of the 21 cases based on a 10% significance level. However, this also implies that the relationship is not present for each currency. In case of the Turkish Lira for example, we find a high mean returns (*Table 7*), but no evidence of a relationship with intervention. Further, the relationship varies over the currencies, which is not unexpected as we are dealing with 21 different country specific characteristics and different intervention policies. A noticeable result is that in particular, the relationship is strongest for the Asian currencies. An explanation might be that Asian emerging markets tend to persistently accumulate foreign exchange reserves to maintain external competitiveness. On the contrary, Latin American countries as Chile and Mexico, have taken measures to reduce the amount of foreign reserves (see BIS (2005)). If we combine this with the fact that the Asian emerging market currencies are only weakly appreciated relative to the rapidly depreciated US dollar over time, this suggests that for these markets, leaning against the wind behavior introduces trends in the exchange rate which are predictable for technical trading rules.

Table 8: Monthly returns and central bank intervention

MA	*N*	$b_{j.0}$		$b_{j.1}$		$b_{j.2}$		R^2
TWD	125	0.004	(3.331)***	0.153	(1.855)*	-0.236	(-2.912)***	6.36%
PEN	90	0.002	(1.751)*	0.020	(0.953)	-0.042	(-0.744)	1.22%
INR	125	0.001	(0.334)	0.167	(1.916)*	-0.082	(-1.991)**	11.78%
MXN	125	-0.004	(-1.525)	0.168	(1.260)	-0.087	(-0.728)	2.02%
ZAR	125	0.001	(0.284)	0.205	(1.906)*	-0.016	(-0.841)	3.53%
CZK	114	-0.006	(-2.108)**	0.431	(3.610)***	-0.071	(-0.561)	13.61%
ILS	113	0.004	(1.95)	-0.111	(-0.861)	0.106	(1.006)	1.75%
THB	112	0.001	(0.459)	0.461	(3.194)***	-0.156	(-1.309)	15.39%
PHP	112	0.003	(1.453)	0.103	(1.457)	-0.118	(-2.842)***	5.15%
IDR	111	0.018	(2.454)**	0.199	(0.675)	-0.878	(-2.226)**	6.80%
KRW	107	-0.002	(-0.879)	0.465	(3.313)***	-0.109	(-0.870)	13.37%
SKK	97	0.001	(0.407)	0.103	(1.534)	-0.036	(-1.485)	3.85%
BRL	93	0.008	(2.145)**	0.000	(0.002)	0.088	(0.624)	0.45%
CLP	86	0.007	(2.303)**	-0.088	(-0.787)	-0.066	(-0.638)	1.01%
COP	86	0.010	(2.957)***	0.035	(0.286)	-0.263	(-2.183)**	2.54%
PLN	79	0.007	(1.41)	-0.089	(-0.358)	-0.186	(-2.030)**	2.33%
TRY	69	0.011	(1.699)*	0.064	(0.547)	-0.297	(-1.589)	4.72%
HUF	66	0.001	(0.182)	-0.034	(-1.266)	0.244	(3.068)***	3.17%
ARS	58	-0.002	(-0.477)	0.076	(2.437)**	0.130	(1.941)**	4.49%
RON	25	0.009	(2.628)**	-0.023	(-0.420)	-0.848	(-2.453)**	3.89%
MYR	16	-0.002	(-1.100)	0.231	(3.223)***	-0.054	(-1.048)	24.64%

SR	*N*	$b_{j.0}$		$b_{j.1}$		$b_{j.2}$		R^2
TWD	125	0.002	(1.964)**	0.274	(2.404)**	-0.187	(-2.099)**	8.95%
PEN	90	0.001	(0.883)	0.031	(1.152)	-0.054	(-0.835)	2.60%
INR	125	0.000	(0.066)	0.166	(1.698)*	-0.072	(-1.580)	10.21%
MXN	125	-0.005	(-1.162)	0.112	(0.612)	-0.046	(-0.363)	0.82%
ZAR	125	-0.002	(-0.420)	0.166	(1.431)	-0.002	(-0.091)	1.92%
CZK	114	-0.005	(-1.746)*	0.416	(3.762)***	-0.050	(-0.364)	13.93%
ILS	113	0.001	(0.386)	-0.087	(-0.927)	0.150	(1.081)	1.53%
THB	112	0.002	(0.970)	0.222	(1.322)	-0.135	(-1.176)	4.45%
PHP	112	0.002	(0.984)	0.104	(1.476)	-0.200	(-3.137)***	9.26%
IDR	111	0.007	(1.168)	0.170	(0.532)	-0.043	(-0.078)	0.49%
KRW	107	-0.002	(-0.987)	0.424	(2.673)***	-0.297	(-1.279)	14.30%
SKK	97	0.000	(0.083)	0.119	(1.476)	-0.038	(-1.394)	4.14%
BRL	93	0.008	(1.459)	-0.004	(-0.054)	0.076	(0.562)	0.32%
CLP	86	0.006	(1.983)**	-0.079	(-0.947)	-0.131	(-2.001)**	1.66%
COP	86	0.007	(1.976)**	0.048	(0.355)	-0.222	(-2.109)**	1.78%
PLN	79	0.001	(0.152)	0.014	(0.054)	-0.173	(-1.705)*	1.84%
TRY	69	0.020	(3.147)***	-0.180	(-1.097)	-0.636	(-3.168)***	9.81%
HUF	66	0.003	(0.730)	-0.064	(-2.532)**	0.201	(2.136)**	3.44%
ARS	58	-0.004	(-0.906)	0.084	(2.323)**	0.141	(1.997)*	4.55%
RON	25	0.008	(2.075)**	-0.111	(-1.454)	-0.325	(-1.141)	2.40%
MYR	16	-0.002	(-0.834)	0.259	(2.786)***	-0.060	(-1.590)	28.27%

This table reports the coefficient estimates of regression (10) for Moving Average and Support and Resistance strategies. The corresponding *t*-statistics are given in parentheses. *N* is the number of observations. *,** and *** indicates significance at 10%, 5% and 1% level respectively.

Table 9: Monthly returns and central bank intervention

MA	***N***	$b_{j.0}$		$b_{j.1}$		R^2
TWD	125	0.002	(2.42)**	0.201	(2.482)**	4.46%
PEN	90	0.001	(1.115)	0.030	(1.258)	0.66%
INR	125	-0.001	(-0.57)	0.205	(2.595)***	9.97%
MXN	125	-0.006	(-2.273)**	0.201	(1.674)*	1.74%
ZAR	125	0.001	(0.23)	0.209	(1.976)**	3.48%
CZK	114	-0.007	(-2.33)**	0.438	(3.705)***	13.50%
ILS	113	0.005	(2.693)**	-0.138	(-1.073)	1.45%
THB	112	0.000	(-0.249)	0.511	(4.063)***	14.67%
PHP	112	0.001	(0.590)	0.145	(2.003)**	3.00%
IDR	111	0.008	(1.797)*	0.392	(1.245)	2.50%
KRW	107	-0.003	(-1.409)	0.496	(3.713)***	13.04%
SKK	97	0.000	(-0.091)	0.117	(1.705)*	3.11%
BRL	93	0.011	(2.250)**	-0.022	(-0.366)	0.04%
CLP	86	0.006	(2.104)**	-0.075	(-0.639)	0.72%
COP	86	0.007	(2.911)***	0.101	(0.854)	0.72%
PLN	79	0.003	(0.855)	-0.009	(-0.034)	0.00%
TRY	69	0.004	(0.823)	0.179	(1.566)	1.91%
HUF	66	0.003	(1.105)	-0.051	(-2.02)	1.22%
ARS	58	0.003	(0.614)	0.024	(0.831)	0.19%
RON	25	0.006	(2.582)**	0.018	(0.306)	0.07%
MYR	16	-0.002	(-1.754)*	0.243	(3.068)***	24.11%

SR	***N***	$b_{j.0}$		$b_{j.1}$		R^2
TWD	125	0.001	(1.350)	0.313	(2.884)***	8.06%
PEN	90	0.000	(0.406)	0.044	(1.600)	1.58%
INR	125	-0.001	(-0.772)	0.199	(2.259)**	8.90%
MXN	125	-0.006	(-1.652)*	0.130	(0.761)	0.74%
ZAR	125	-0.002	(-0.457)	0.166	(1.461)	1.92%
CZK	114	-0.005	(-2.093)**	0.421	(3.894)***	13.87%
ILS	113	0.002	(1.157)	-0.125	(-1.237)	1.02%
THB	112	0.001	(0.504)	0.265	(1.552)	3.92%
PHP	112	-0.001	(-0.697)	0.175	(2.142)**	3.85%
IDR	111	0.006	(1.062)	0.179	(0.584)	0.48%
KRW	107	-0.005	(-2.075)**	0.510	(3.596)***	12.18%
SKK	97	-0.001	(-0.343)	0.133	(1.648)*	3.44%
BRL	93	0.010	(1.749)*	-0.023	(-0.370)	0.04%
CLP	86	0.004	(1.533)	-0.053	(-0.636)	0.40%
COP	86	0.004	(1.721)*	0.104	(0.792)	0.65%
PLN	79	-0.002	(-0.461)	0.088	(0.342)	0.32%
TRY	69	0.005	(0.946)	0.067	(0.419)	0.20%
HUF	66	0.004	(1.301)	-0.079	(-2.545)**	2.37%
ARS	58	0.001	(0.160)	0.028	(0.852)	0.21%
RON	25	0.007	(2.411)**	-0.096	(-1.352)	1.89%
MYR	16	-0.002	(-1.319)	0.272	(2.845)***	27.66%

This table reports the coefficient estimates of regression (11) for Moving Average and Support and Resistance strategies. The corresponding *t*-statistics are given in parentheses. *N* is the number of observations. *,** and *** indicates significance at 10%, 5% and 1% level respectively. *N* is the number of observations

Table 10: Monthly returns and central bank intervention

MA	*N*	$c_{j.1}$		$c_{j.2}$		$b_{j.1}$		$b_{j.2}$		R^2
TWD	125	0.002	(1.291)	0.005	(2.439)**	0.218	(2.432)**	-0.333	(-2.908)	7.40%
PEN	90	0.002	(1.320)	0.002	(0.811)	0.020	(0.878)	-0.042	(-0.618)	1.22%
INR	125	0.003	(0.832)	-0.001	(-0.822)	0.111	(0.885)	-0.046	(-1.339)	12.97%
MXN	125	-0.006	(-0.826)	-0.003	(-0.947)	0.199	(0.913)	-0.118	(-0.974)	2.11%
ZAR	125	0.001	(0.072)	0.002	(0.364)	0.215	(1.647)*	-0.019	(-0.883)	3.56%
CZK	114	-0.004	(-1.065)	-0.014	(-1.861)*	0.389	(3.221)***	0.050	(0.339)	14.74%
ILS	113	0.002	(0.596)	0.007	(2.179)**	-0.036	(-0.285)	-0.051	(-0.318)	2.97%
THB	112	-0.004	(-1.006)	0.006	(1.533)	0.613	(3.451)***	-0.314	(-2.036)	17.61%
PHP	112	-0.001	(-0.263)	0.007	(2.102)**	0.181	(2.256)**	-0.189	(-3.117)	7.56%
IDR	111	0.029	(3.446)***	0.002	(0.182)	0.007	(0.026)	-0.426	(-0.939)	9.00%
KRW	107	0.002	(0.476)	-0.006	(-1.586)*	0.360	(2.008)**	0.026	(0.191)	14.68%
SKK	97	0.006	(1.786)*	-0.006	(-1.482)*	0.039	(0.481)	-0.003	(-0.106)	7.04%
BRL	93	0.010	(1.834)*	0.007	(0.705)	-0.018	(-0.322)	0.108	(0.615)	0.53%
CLP	86	0.006	(1.644)	0.009	(1.839)*	-0.070	(-0.574)	-0.104	(-0.865)	1.26%
COP	86	0.010	(2.098)**	0.009	(2.243)**	0.019	(0.140)	-0.238	(-1.671)	2.58%
PLN	79	0.015	(1.915)*	0.001	(0.205)	-0.261	(-0.971)	-0.087	(-0.677)	4.99%
TRY	69	0.015	(1.672)*	0.007	(0.667)	0.012	(0.080)	-0.224	(-0.775)	5.03%
HUF	66	0.001	(0.291)	-0.001	(-0.104)	-0.037	(-1.749)	0.272	(2.166)	3.22%
ARS	58	-0.001	(-0.108)	-0.011	(-3.130)***	0.060	(2.116)**	0.235	(3.367)	8.68%
RON	25	0.010	(2.316)**	0.002	(0.086)	-0.040	(-0.652)	-0.394	(-0.287)	4.75%
MYR	16	0.003	(2.270)**	-0.008	(-2.262)**	0.103	(1.390)	0.103	(0.975)	41.45%

SR	*N*	$c_{j.1}$		$c_{j.2}$		$b_{j.1}$		$b_{j.2}$		R^2
TWD	125	0.000	(-0.130)	0.005	(3.011)***	0.366	(2.297)**	-0.325	(-3.617)***	8.06%
PEN	90	0.001	(0.689)	0.001	(0.743)	0.033	(1.221)	-0.059	(-0.860)	1.58%
INR	125	0.003	(0.731)	-0.002	(-1.298)	0.099	(0.705)	-0.029	(-0.807)	8.90%
MXN	125	-0.006	(-0.834)	-0.003	(-1.222)	0.152	(0.579)	-0.084	(-0.775)	0.74%
ZAR	125	-0.001	(-0.095)	-0.003	(-0.564)	0.149	(0.976)	0.002	(0.092)	1.92%
CZK	114	-0.004	(-0.962)	-0.008	(-1.411)	0.396	(3.413)***	0.008	(0.052)	13.87%
ILS	113	-0.003	(-1.100)	0.005	(1.709)*	0.014	(0.162)	-0.061	(-0.350)	1.02%
THB	112	-0.001	(-0.179)	0.006	(1.328)	0.325	(1.314)	-0.242	(-1.320)	3.92%
PHP	112	-0.003	(-1.055)	0.008	(2.660)**	0.206	(2.442)**	-0.293	(-3.826)***	3.85%
IDR	111	0.022	(2.791)***	-0.019	(-1.696)*	-0.123	(-0.400)	0.650	(0.923)	0.48%
KRW	107	-0.001	(-0.450)	-0.004	(-0.894)	0.392	(2.123)**	-0.250	(-0.950)	12.18%
SKK	97	0.002	(0.383)	-0.001	(-0.358)	0.103	(1.100)	-0.030	(-1.038)	3.44%
BRL	93	0.010	(1.589)	0.005	(0.506)	-0.028	(-0.351)	0.103	(0.629)	0.04%
CLP	86	0.003	(0.881)	0.012	(2.405)**	-0.027	(-0.343)	-0.237	(-2.824)***	0.40%
COP	86	0.009	(1.694)*	0.004	(0.918)	0.003	(0.021)	-0.151	(-0.981)	0.65%
PLN	79	0.013	(1.610)	-0.008	(-0.991)	-0.247	(-1.018)	-0.023	(-0.168)	0.32%
TRY	69	0.028	(2.418)**	0.011	(1.014)	-0.296	(-1.167)	-0.472	(-1.650)	0.20%
HUF	66	0.000	(-0.085)	0.009	(1.392)	-0.043	(-2.494)**	0.048	(0.476)	2.37%
ARS	58	-0.003	(-0.642)	-0.014	(-3.160)***	0.070	(2.679)**	0.258	(3.391)***	0.21%
RON	25	0.010	(1.836)*	-0.004	(-0.221)	-0.140	(-1.837)*	0.439	(0.365)	1.89%
MYR	16	0.004	(1.574)	-0.009	(-2.175)**	0.109	(0.943)	0.123	(1.174)	27.66%

This table reports the coefficient estimates of regression (12) for Moving Average and Support and Resistance strategies. The corresponding *t*-statistics are given in parentheses. *N* is the number of observations. *,** and *** indicates significance at 10%, 5% and 1% level respectively. *N* is the number of observations.

Table 11: Monthly returns and central bank intervention

	$b_{j.0}$		$b_{j.1}$		$b_{j.2}$		R^2
Vol.W.	-0.002	(-1.162)	0.345	(3.413)***	-0.067	(-2.077)**	19.51%

Panel	**MA**		**SR**	
c_1	0.004	(4.101)***	0.003	(3.029)***
c_2	0.001	(0.824)	0.000	(0.448)
c_3	0.001	(1.097)	0.001	(0.918)
c_4	-0.004	(-1.881)*	-0.004	(-1.942)*
c_5	0.004	(1.045)	0.000	(0.049)
c_6	-0.001	(-0.232)	0.001	(0.433)
c_7	0.004	(2.399)**	0.001	(0.529)
c_8	0.005	(3.076)***	0.004	(1.945)*
c_9	0.002	(1.342)	0.001	(0.326)
c_{10}	0.013	(2.234)**	0.009	(1.477)
c_{11}	0.002	(1.217)	0.000	(0.072)
c_{12}	0.001	(0.526)	0.002	(0.512)
c_{13}	0.008	(1.847)*	0.007	(1.512)
c_{14}	0.004	(1.431)	0.003	(1.086)
c_{15}	0.007	(2.992)***	0.005	(1.844)*
c_{16}	0.003	(0.851)	-0.002	(-0.478)
c_{17}	0.007	(1.459)	0.006	(1.123)
c_{18}	-0.002	(-0.71)	-0.009	(-2.391)**
c_{19}	0.002	(0.453)	0.001	(0.122)
c_{20}	0.004	(1.261)	0.003	(0.692)
c_{21}	0.000	(-0.005)	0.001	(0.455)
γ_1	0.097	(2.654)***	0.073	(1.89)*
γ_2	-0.047	(-1.78)*	-0.042	(-1.772)*
R^2		2.94%		1.74%

This table reports the coefficient estimates of regression (10) for the volatility weighted portfolio and regression (13) for Moving Average and Support and Resistance strategies. The corresponding *t*-statistics are given in parentheses. *N* is the number of observations. *,** and *** indicates significance at 10%, 5% and 1% level respectively.

4.2. Intervention and macro variables

In Section 4.1 we find that a relation between central bank intervention and technical trading rule profits is plausible. However, other factors might simultaneously drive these two processes, such that intervention does in fact not cause those profits. This is known as the simultaneity problem. In this section, we attempt to address this issue by regressing the monthly trading rule profits on the six macroeconomic variables discussed in Section 2.4. The procedure is similar to the procedure in Szakmary and Mathur (1997).

In contrast to technical analysts, fundamentalists believe that changes in the exchange rate are associated with changes in macroeconomic "fundamentals". In general, fundamentals are the underlying real factors, usually macroeconomic variables that determine the value of an asset. According to this theory, foreign exchange traders react slowly on changes in fundamentals, which is displayed in the trending behavior at times when major macroeconomic fundamental variables change, and that central banks react to those changes by intervening. In this view, changes in macroeconomic variables drive both intervention and trading behavior in exchange rates.

4.2.1 Methodology

We are interested in changes in macroeconomic variables. Therefore, for each emerging market country we use the growth rate of the variables relative to the United States:

$$X = log\left(\frac{X_{US,t}}{X_{EM,t}}\right) - log\left(\frac{X_{US,t-1}}{X_{EM,t-1}}\right) \tag{14}$$

The macroeconomic variables are available at a monthly frequency except for GDP, which is reported quarterly. In case of GDP, we use the quarterly growth rates for each month within a quarter. Next, we transform the relative growth rates to absolute deviation from the mean:

$$X = abs(X - mean(X)) \tag{15}$$

We use the absolute deviation because we investigate whether positive or negative changes in fundamental variables are positively related to trading rule profits. In this setting, we assume that the more the variable deviates from a certain average level, the more the exchange rate need to change, the more likely it shows trending behavior which can be picked up by technical trading rules. Hence we expect a positive relationship between changes in macroeconomic variables and trading rule profits. Because the publication of macroeconomic variables is often delayed, we also consider for each variable a one period lag and in case of GDP a three period (quarterly) lag. Further, we also consider the contemporaneous observations of the IVL_t and IVN_t variable as well to see what their performance is when controlling for other variables. Thus in total, we have 14 explanatory variables available for our regression tests. Correlation matrices (not reported) show that the IVL_t variable is not correlated with the fundamental variables with values between -0.2 and +0.2 for all examined countries. The correlation among other variables is generally in the same range, although there are rare occasions where it is as high as 0.7. The same monthly trading rule returns as before are used as dependent variable.

For each country, we estimate the coefficients independently from the other countries. Due to the small number of observations compared to the number of explanatory variables for Romanian Leu and the Malaysian Ringgit, we exclude these countries from our analysis. We consider an iterative selection procedure to find the 'optimal' model. There are several procedures that can be used for this purpose, like the *bottom-up approach* or the *top-down approach* and *backward elimination*. We apply the latter method as this approach is more suitable if the variables cannot be ordered in terms of importance. This method starts with a full model, which means all possibly relevant explanatory variables are included in the regression in the first estimation round. Next, the least significant variable is deleted. Then the model is estimated again with the remaining variables. This process is repeated until all remaining variables are significant at 10% significance level. While the variables can be significant, it may still have a meaningless coefficient. Therefore, we also eliminate regressors on the basis of economic significance. The choice of the threshold value for economic significance is not a clear cut decision. Further, the estimated coefficients are sensitive to scaling of the variables. However, all the variables in our case are in percentage changes. We set the threshold value equal to 0.01, meaning that deviations with an effect smaller than 0.01 on the returns will be excluded from the model.

Because we consider many variables at a significance level of 10%, some variables may be statistically significant even if there is no relationship between changes in fundamentals and trending behavior. Therefore, another criterion we use to evaluate significance is whether or not the sign is also correct and the frequency a variable is included in the model.

4.2.2 Empirical Results

The evaluation of the performance of the variables are based on the results in *Table 12*, which reports the frequency a variable is present in the 19 final models and the frequency it has a positive or a negative sign. The final models resulting from backward elimination procedure are given in *Appendix A2* Note that for a few countries, none of the variables can explain the returns. Based on our evaluation criteria, we generally find that the macro-economic variables cannot explain the trading rule profits. In case of the Moving Average returns, we see that WPI_t performs relatively well, as it is included in the final model three times and its coefficient always has the correct positive sign. However, the performance of our IVL_t variable is still the best, consistent for *both* trading strategies. We see that, even accounting for other variables, the IVL_t variable appears most frequent in the final models with 8 times, all with the correct positive sign for the Moving Average returns, and 7 times with six positive signs for the Support and Resistance returns. Further, the currencies for which IVL_t variable is in the final model are comparable to the currencies for which $b_{j,1}$ is significant in *Table 8*. Also, we see that the IVN_t variable also performs reasonably well. Hence, the results indicate that changes in macroeconomic variables are not able to explain the trading rule returns. Therefore, it is unlikely that macroeconomic fundamentals drive both intervention and trending behavior in the exchange rate.

Table 12: backward elimination results

Variable	MA	#	+	-	SR	#	+	-
IVL_t		8	8	0		7	6	1
IVN_t		10	2	8		6	1	5
CPI_t		5	2	3		4	1	3
WPI_t		3	3	0		3	2	1
IMP_t		1	0	1		2	0	2
EXP_t		4	3	1		5	3	2
MO_tN		6	3	3		4	1	3
GDP_t		5	1	4		2	1	1
CPI_{t-1}		3	1	2		4	1	3
WPI_{t-1}		2	1	1		5	2	3
IMP_{t-1}		5	3	2		3	2	1
EXP_{t-1}		4	0	4		4	1	3
MON_{t-1}		3	1	2		3	1	2
GDP_{t-3}		6	4	2		5	3	2

This table contains the results of backward elimination procedure for 19 countries, according to our evaluation criterion. '#' means the frequency the variable is in the final model, "+" ("-") means the number of times it has a positive (negative) sign.

5 Case study: Removing intervention periods for Peru and Turkey

From all countries in our sample, detailed central bank intervention data is only publicly available for Peru and Turkey. In this Section, we perform a case study for these two markets and follow the methodology of LeBaron (1999) by analyzing the trading rule returns after removing the intervention periods from the sample. Thus, we now focus more on the impact of intervention on trading rule profits. In order to do so, we use the *daily* return series obtained from Section 3.

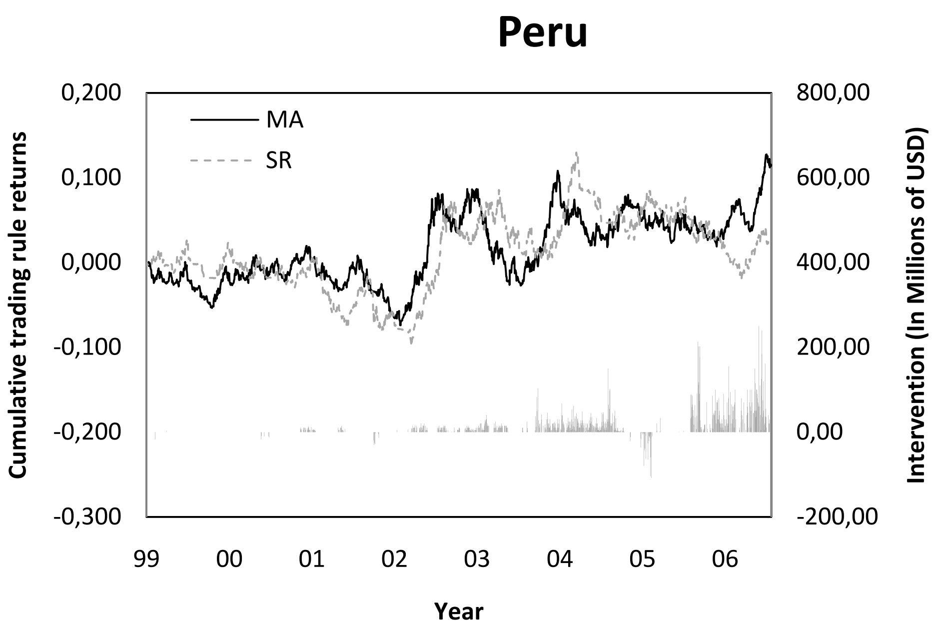
5.1 Removing returns on days of intervention

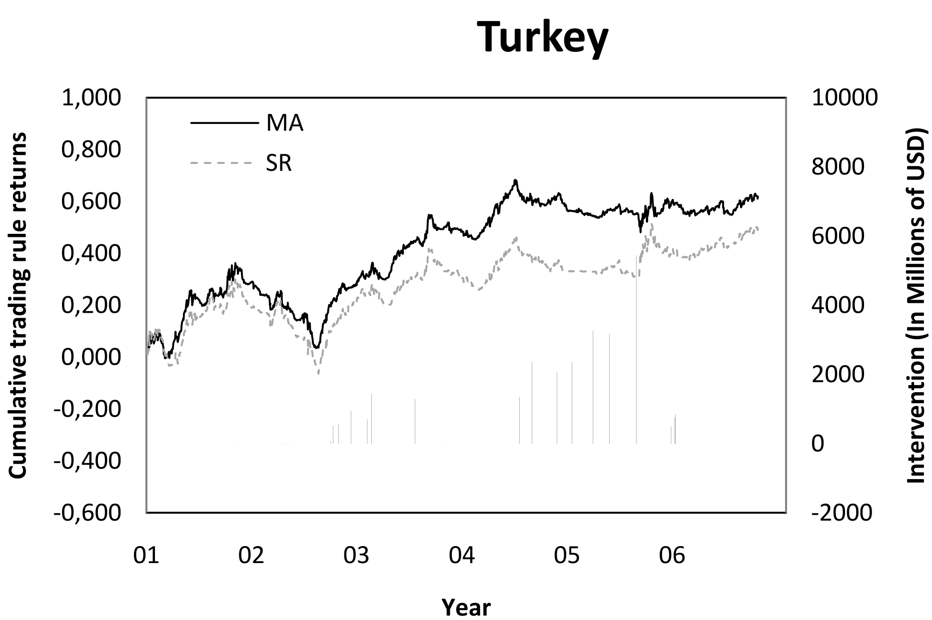
The idea behind this procedure is that on days of intervention, exchange rates are more predictable by technical trading rules. Thus, removing the returns on intervention days, we hypothesize lower profitability of our trading rules. The procedure is as follows, when intervention occurs at day *t*, we remove the trading rule return of *t-1* to *t*. Next we compute the statistics over the new series by repeating the experiments in Section 3. This procedure can be considered to be more exact than the procedure with a proxy from the previous section because we are working on daily basis and actual intervention data. On the other hand, we focus on the specific intervention days while the impact of intervention may have a longer-lasting effect.

For a first impression, we plot the cumulative trading rule returns against intervention activity over time in *Figure 2*. We see that in case of Peru, the cumulative returns increase in periods of intervention. This relationship is less clear for Turkey as the CBRT hardly intervened. For more detailed results, *Table 13* shows the results of the annualized daily mean, standard deviation, Sharpe ratio and bootstrapped *p*-value when returns on the intervention days are removed for both trading rules. For comparison, *Table 13* also repeats the original values, obtained in Section 3.2. In case of Peru, we see that the annualized mean return has declined dramatically. The mean return has decreased from 1.847 to 0.731 for Moving Average strategies. For the Support and Resistance rule, the mean return has even become negative as it drops from 1.178 to -0.361. Further, we see that the Sharpe ratio decreased and the bootstrapped *p*-value has gone up. On the other hand, the results for Turkey are weaker, which is more or less expected because they hardly intervened in our sample period. Still, we find a decrease in mean return of 2% on annual basis and an increase in *p*-value for both rules.

For Peru and Turkey, we do not find a (significant) relationship between trading rule profitability and intervention in section 4.1. Thus, we see that different methods may lead to different conclusions, which is the case for Peru. In case of Turkey, the significant constant term for regression (13) in *Table 8* is somewhat comparable to the mean return remaining after removing the returns on intervention days in *Table 13*, as both indicate the mean return that is not due to intervention.

Figure 2: cumulative return and intervention





This figure illustrates the cumulative returns of Moving Average strategies and Support and Resistance strategies and intervention over time.

Table 13: Trading rule statistics with no intervention periods

Peru	Rule	N	Mean	std	Sharpe	*p*
no int	MA	1283	0.731	3.381	0.216	0.478
no int	SR	1283	-0.361	3.315	-0.109	0.720
Full sample	MA	1977	1.847	3.074	0.601	0.196
Full sample	SR	1977	1.178	2.995	0.393	0.451
Turkey						
no int	MA	1484	8.261	13.858	0.596	0.356
no int	SR	1484	6.108	14.145	0.432	0.576
Full sample	MA	1519	10.685	13.928	0.767	0.215
Full sample	SR	1519	8.605	14.212	0.605	0.301

This table reports the statistics of the returns after removing the returns on intervention days for Moving Average and Support and Resistance rules. “no int” means that the intervention days are removed from the sample.

5.2 Robustness test

An effect we should not disregard is the effect of intervention clustering. Removing subsequent days of returns can lower returns, irrespective whether intervention has occurred or not. That is, trending behavior is not necessarily due to intervention. In particular interventions in Peru are clustered, as reported in *Table 5* in Section 2.3. To take this effect into account, we compare the results of the original intervention series to the results of randomly simulated intervention series. The procedure is as follows. We assume that interventions follow a Markov Process and we construct two-states Markov processes of interventions, using the transition probabilities from *Table 5*. These random series contain only values of 0 and 1 for no intervention and intervention respectively. These Markov intervention series contain the same degree of clustering as the original intervention series. Next, we remove returns according to the generated intervention series and compute the mean return. This procedure is repeated 1000 times. For evaluation, we define the Markov *p*-value as the fraction of simulated series that leads to a lower return than the original series, after removal of returns.

Table 14 reports the result of removing the simulated intervention series. It contains the Markov mean, which is the average over the 1000 series from which we randomly removed returns, the Markov standard deviation and the Markov *p*-value. We see for both countries that the Markov mean is close to the original mean. Moreover, the Markov *p*-values are low, which suggest that removing returns on intervention days is “significantly” different than from randomly removing returns. In the case of Turkey, the Markov *p*-values are even close to zero. Thus, although the number of interventions is low, the returns on those days are substantial. This may be due to the large magnitude of intervention by the CBRT, as reported in *Table 5* in section 2.3.

Table 14: Markov comparisons

Peru	Rule	Mean no int	Mean	Markov mean	Markov std	Markov *p*
	MA	0.731	1.847	1.816	0.049	0.085
	SR	-0.361	1.178	1.143	0.047	0.026
Turkey						
	MA	8.261	10.685	10.693	0.043	0.000
	SR	6.108	8.605	8.612	0.044	0.001

This table reports the statistics of the returns after removing the simulated intervention series. Mean and Mean no int repeats the values of returns with and without intervention periods from earlier tables. The Markov mean and the Markov std is the mean and standard deviation over the 1000 simulated series. The Markov *p* is the fraction of simulated series leading to a lower trading rule return, compared to the no intervention series from the original intervention data.

5.3 sign comparisons

To see what mechanism is driving the results above, we also investigate the dynamics between the trading rule predictability and intervention. We do this by comparing the signs of trading rule signal, intervention, and currency return. For this analysis, the sample is restricted to days on which intervention occurs. More specifically, we consider following three cases of sign comparisons: First, we compare the sign of trading rule signal at *t-1* with the sign of intervention at *t*. This indicates the behavior of the central bank with respect to the behavior of technical traders in the previous period. Second, we compare the sign of trading rule signal at *t-1* with the sign of currency return from *t-1* to *t*. This indicates the degree of predictability of the exchange rate. Third, we compare the sign of intervention at *t* with the sign of currency return from *t-1* to *t*. This gives information of the direction of the exchange rate movement with respect to the direction of intervention[9]. Next, we compute the probability (fraction) of *opposite* sign for the first case, the probability of *equal* sign for the second case and the probability of *opposite* sign for the third case[10]. For evaluation we consider the Pesaran-Timmermann test which determines whether these probabilities significantly differs from the expected "benchmark" probabilities in case the signs are independent of each other, see Pesaran and Timmermann (1992) and *Appendix A3*. The resulting *PTNK*-statistic converges in distribution to *N*(0,1) and square of the *PTNK*-statistic is asymptotically equal to the $\chi^2(1)$-statistic. Again, we consider significance levels of 1%, 5% and 10%.

The results of the three sign comparisons are given in *Table 15*. This table shows the probability (fraction) of *opposite* sign for Signal-Intervention, *equa*l sign for Signal-Return, and *opposite* sign for Intervention-Return with the corresponding benchmark probabilities in case of independent signs, and

[9] Note that the central bank may be induced to reverse the direction of exchange rate, instead of reacting to the exchange rate by leaning against the wind. If this is the case, then intervention is not responsible for generating returns.

[10] LeBaron (1999) computes probabilities of *equal* sign for the three cases. This is because the exchange rate is expressed differently than in our case. We account for this, in order to have the same interpretation of the results.

the *PTNK*-statistics. We see that for Signal-Intervention, the probability is very large with values above 0.8 for both currencies and both rules. This significantly differs from the probability in case of the signs of trading rule signal and intervention are independent of each other. This result is consistent with leaning against the wind intervention as central bank goes into the opposite direction of (technical) traders. In case of Signal-Return, we see that for both countries, the probabilities are higher than the benchmarks and both rules. This indicates that the trading rules are able to predict the exchange rate movement on intervention days and that the reduction of returns after removing intervention periods is not due to a few high returns in those periods. In case of Peru however, the predictive ability of Moving Average rules are weaker, as the *PTNK*-statistic is not significant in this case. Finally, we find high probabilities and significant *PTNK*-statistics for Intervention-Return for both countries and both rules. This is also in line with leaning against the wind behavior in the sense that on the day of intervention, the exchange rate is moving oppositely to intervention.

Further, the values of Moving Average strategies and Support and Resistance strategies are about the same. If we combine this result with the results in *Table 13*, we see that both the performance of both rules are about equally well during intervention periods, although the performance over the whole sample is lower for Support and Resistance strategies than for Moving Average strategies. This suggests that exchange rate movements on intervention days seem to be more easily detectable.

Table 15: Sign comparisons

Peru	**Rule**	**N**		**Signal-Intervention**	**Signal-Return**	**Intervention-Return**
	MA	694	p	0.862	0.585	0.631
			p*	0.770	0.578	0.614
			PTNK	13.061***	0.459	2.067**
	SR	694	p	0.837	0.601	0.631
			p*	0.747	0.572	0.614
			PTNK	12.260***	1.919*	2.067**
Turkey						
	MA	21	p	0.810	0.714	0.905
			p*	0.551	0.551	0.592
			PTNK	2.767***	1.747*	3.600***
	SR	21	p	0.810	0.714	0.905
			p*	0.551	0.551	0.592
			PTNK	2.767***	1.747 *	3.600 ***

This table contains the probabilities of opposite sign between trading rule signal and intervention, equal signs between trading rule signal and currency return, and opposite signs between intervention and currency return respectively, all conditioned on days on which intervention occurred. 'p' and 'p*' denotes the real and benchmark probability respectively. The table also reports the *PTNK*-statistics. *,** and *** indicates significance at 10%, 5% and 1% level respectively.

5.4 Volatility as a common factor

A factor that might drive both predictability and intervention is volatility. Volatility is the variability of asset prices (or returns). High volatility might add extra risk to dynamic strategies implying a higher risk premium, and therefore a greater predictability. At the same time, an important motivation for central bank interventions is to dampen the volatility. Further, we see in *Table 7* that the high mean return is accompanied by high volatility in case of Turkey. To address the simultaneity problem in this case we follow LeBaron (1999) and investigate whether volatility can explain the trading rule returns.

One type of model that is popular and widely used is the GARCH model, introduced by Bollorslev (1986). GARCH models can account for stylized facts of returns like a non-normal distribution, no significant autocorrelations in returns and small but slowly declining correlations in the squared returns. The last property is also known as volatility clustering as periods with large returns alternate with periods with small returns. We consider a GARCH (1,1) model to model the volatility over time for both countries. Further, we consider a Student-*t* distribution as the returns are not normally distributed:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{16}$$
$$\varepsilon_t^2 = (r_t - \mu)^2$$

Where, h_t is the time-varying (conditional) variance, r_t the currency return and μ is the unconditional mean of the return and $\varepsilon \sim t(0, \sigma, \mathrm{df} = \nu)$. Next, we remove returns on days corresponding to the percentage of most volatile periods from h_t, equal to the probability of intervention. More specifically, we remove the returns on 694 and 21 days of which the values of h_t is the highest for Peru and Turkey respectively.

Table 16 reports the statistics of the returns after removing the returns on days with the highest volatility. The table also contains the values of the original returns. For both countries, we see that after removing the most volatile periods, the mean returns have not changed much. Moreover, for Support and Resistance rules the mean returns have actually increased. This suggests that volatility is unlikely driving both Intervention and predictability in our cases.

Table 16: Trading rule statistics. where highest volatility periods are removed

Peru	Rule	N	Mean	std	Sharpe	*p*
no vol	MA	1283	1,757	2,132	0,824	0,188
no vol	SR	1283	1,307	2,077	0,629	0,410
Full sample	MA	1977	1,847	3,074	0,601	0,196
Full sample	SR	1977	1,178	2,995	0,393	0,451
Turkey						
no vol	MA	1283	8,384	13,556	0,618	0,476
no vol	SR	1283	10,837	13,790	0,786	0,498
Full sample	MA	1519	10,685	13,928	0,767	0,215
Full sample	SR	1519	8,605	14,212	0,605	0,301

This table reports the statistics of the returns after removing the fraction of returns on days with highest volatility equal to probability of intervention. “no vol” means that the most volatile days are removed from the sample.

5.5 Summary

To summarize, removing the returns on intervention days significantly lowers the mean returns for our two cases. However, other factors might also contribute as in case of Turkey, the resulting mean returns are still relativity high after removal of intervention periods. Also, based on the results of Peru we can say that when intervention is clustered over a period of time, the exchange rate movements are smoother than at other periods. It suggests that persistent interventions introduce trends in the exchange rate movements that can be detected by technical trading rules.

Based on this empirical analysis, we conclude that trading rule profits are related with central bank intervention for Peru and Turkey. However, for Turkey this is only a weak relationship. Further, by comparing the results of the analysis in this Section with the results of the analysis in Section 4, we find that different methods may lead to different conclusions. Possible reasons that contribute to this are that the proxies we use in Section 4 are not perfect and the difference in frequency of the data, which is also discussed in Section 4.1.

6 Conclusion

Nowadays, emerging market currencies have become tradable and data are increasingly available. Research by Pukthuanthong-Le et al. (2008) and De Zwart et al (2009) has shown that trading rules can be profitable in these markets. To our knowledge, empirical research on the relationship between technical trading rule profits and central bank intervention has primarily focused on developed currency markets. No research however, has investigated the relationship between trading rule profits and central bank intervention for emerging currency markets. Intervention in emerging markets can be more effective than in developed markets because: (1) the larger size of interventions relative to market turnover, (2) informational advantage of central banks over local participants on fundamentals, (3) and greater impact of central banks in the markets due to capital controls that limits access to international markets.

In this research we investigate the relationship between the profitability of technical trading rules and central bank intervention for 21 emerging market currencies with a floating rate regime over the period 1997-2007. We confirm earlier results of profitability by using Moving Average and Support and Resistance strategies. Further, we find that the performance of Moving Average strategies is generally higher than of Support and Resistance. We perform two analyses to research the relationship between the profits and central bank intervention. First, we use changes in foreign exchange reserves, for which the data are available for all currencies, as a proxy for intervention. We follow the procedure of Szakmary and Mathur (1997) by performing regression tests and analyze leaning against the wind intervention. Second, we perform a case study for Peru and Turkey using actual intervention data. For the other markets, the data is not publicly available. In this part we follow the procedure of LeBaron (1999) by excluding intervention periods from the sample and analyze the profits without intervention days. In both analyses, we find evidence that technical trading rule profits are related to central bank intervention. However, looking at individual countries, this is not always the case or intervention only partly explains the profits. Further, we cannot draw conclusions about causality, which is if intervention is really generating the returns. We therefore conclude that a relationship between technical trading rule profits and central bank intervention in emerging currency markets is plausible.

If we compare our findings to those from earlier studies on developed currency markets, the relationship between central bank intervention and trading rule profits seems to be less persistent across emerging markets than across developed markets. On the other hand, these studies only focus on a limited number of developed markets, while we cover a broad range of emerging markets.

The limited availability of data is a drawback in this research. In particular, the regressions we perform with relatively limited observations. For further research, more intervention data could lead to more accurate estimates and more detailed results. Furthermore, one can focus more on the causality, by performing a similar analysis as in Neely (2002) with higher frequency (intraday) exchange rate data.

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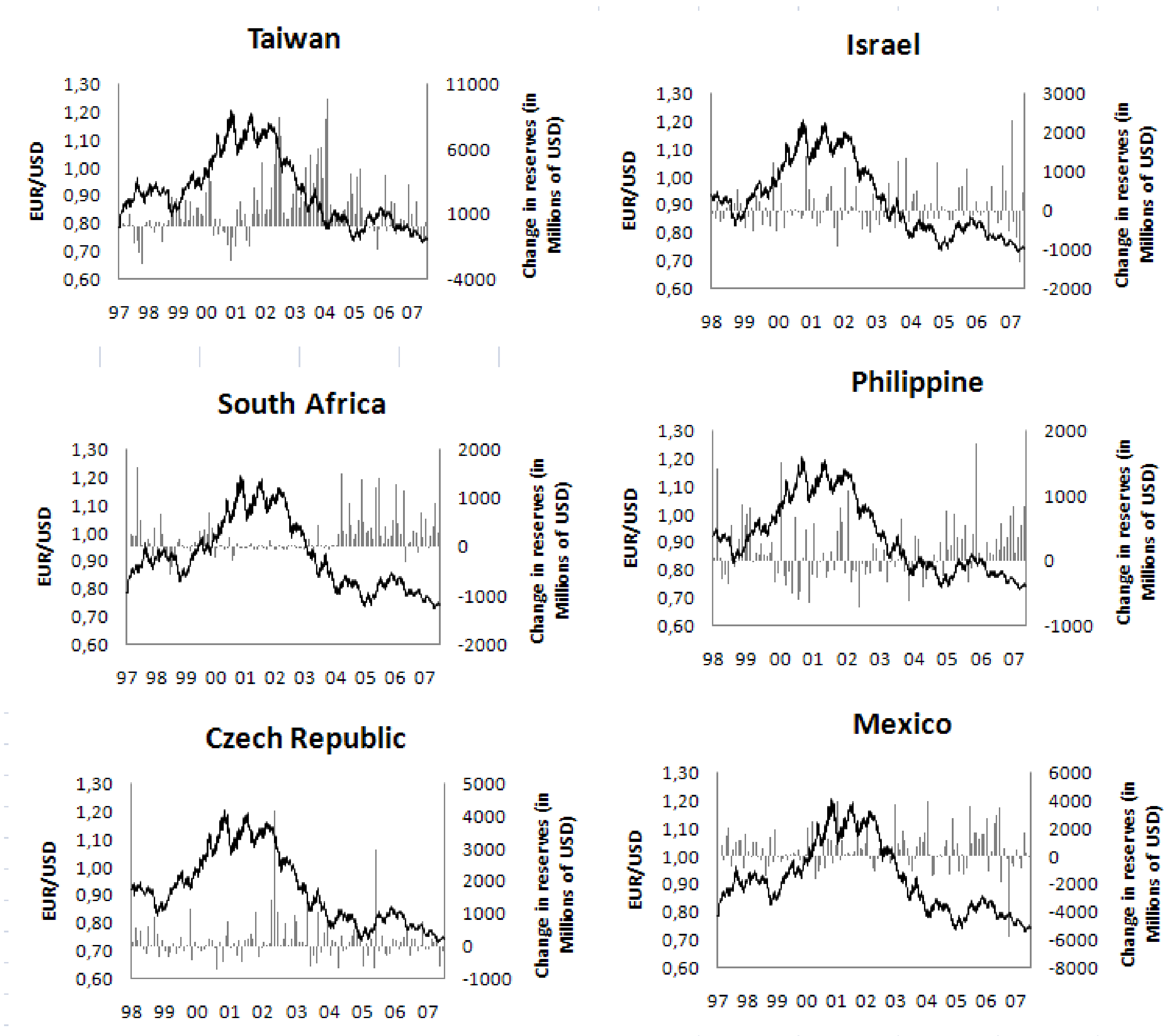
8 Appendix

Appendix A1: The EUR/USD and changes in reserves over time



This figure illustrates, for several currencies, the behavior of the EUR/USD rate and changes in foreign exchange reserves (in Millions of USD) over time.

Appendix A2: final models

MA	R^2				**Variables**				
TWD	11.18%	-0.001	+ 0.157IVL_t	-0.285IVN_t	+0.027EXP_t	+0.081GDP_{t-3}			
		(-0.664)	(1.778)	(-3.733)	(1.867)	(2.926)			
PEN	10.75%	0.000	+0.310CPI_t	-0.324MON_t	+0.019IMP_{t-1}				
		(-0.173)	(2.131)	(-3.407)	(1.828)				
INR	20.16%	0.009	+0.149IVL_t	-0.09IVN_t	-0.044GDP_t	-0.065CPI_{t-1}	-0.538MON_{t-1}		
		(2.903)	(1.807)	(-1.672)	(-3.026)	(-2.749)	(-2.794)		
MXN	6.32%	0.008	+0.222IVL_t	-0.145CPI_t	-0.126EXP_t				
		(1.591)	(1.906)	(-2.067)	(-1.863)				
ZAR	9.64%	-0.018	+0.297IVL_t	+1.651MON_t	+0.645GDP_{t-3}				
		(-2.483)	(2.647)	(2.195)	(1.950)				
CZK	15.44%	-0.003	+0.449IVL_t	-0.181CPI_t					
		(-0.78)	(3.242)	(-1.733)					
ILS	1.66%	0.007	-0.156GDP_t						
		(3.676)	(-2.159)						
THB	21.51%	0.010	+0.312IVL_t	-0.21IVN_t	+0.069EXP_t	-0.811MON_t	-0.243GDP_{t-3}		
		(1.928)	(2.472)	(-2.170)	(2.385)	(-2.04)	(-2.356)		
PHP	5.63%	0.002	-0.146IVN_t	+0.208WPI_{t-1}					
		(0.923)	(-3.365)	(1.911)					
IDR	35.87%	-0.018	-0.891IVN_t	+0.897WPI_t	-2.487MON_t	+3.322MON_{t-1}	+0.54GDP_{t-3}		
		(-1.974)	(-3.225)	(2.150)	(-2.463)	(3.573)	(2.774)		
KRW	15.49%	-0.001	+0.461IVL_t	+0.056GDP_t	-0.071GDP_{t-3}				
		(-0.272)	(3.554)	(1.758)	(-2.207)				
SKK	10.35%	0.017	-0.07IVN_t	-0.149GDP_t	-0.087IMP_{t-1}				
		(3.479)	(-2.539)	(-2.117)	(-2.344)				
BRL	17.86%	-0.006	+0.23EXP_t	+0.215IMP_{t-1}	-0.233EXP_{t-1}				
		(-0.645)	(2.101)	(2.150)	(-1.809)				
CLP	22.96%	0.016	+1.221CPI_t	+0.678WPI_t	-1.459CPI_{t-1}	-0.84WPI_{t-1}	-0.059EXP_{t-1}		
		(2.115)	(2.472)	(2.328)	(-2.985)	(-3.732)	(-2.177)		
COP	6.55%	0.016	-0.231IVN_t	-0.964MON_{t-1}					
		(2.852)	(-1.823)	(-1.764)					
PLN	8.55%	0.004	-0.139IMP_t	+0.111IMP_{t-1}					
		(1.066)	(-2.543)	(1.706)					
TRY	26.68%	0.007	-0.466IVN_t	+1.084MON_t	-0.146IMP_{t-1}	-0.171EXP_{t-1}			
		(0.737)	(-2.04)	(2.463)	(-3.766)	(-2.253)			
HUF	10.53%	0.002	+0.335IVN_t	+1.459MON_t	-0.117GDP_t				
		(0.398)	(2.912)	(2.039)	(-1.999)				
ARS	44.20%	-0.014	+0.098IVL_t	+0.105IVN_t	-0.364CPI_t	+0.471WPI_t	+0.457CPI_t	-0.098EXP_{t-1}	+0.088GDP_{t-3}
		(-2.012)	(2.130)	(1.977)	(-5.131)	(1.667)	(7.645)	(-2.307)	(1.740)

This table contains the final models for Moving Average returns resulting from the backward elimination procedure described in Section 5.1. *t*-statistics are given in parentheses.

Appendix A2 (*panel 2*)

SR	R^2				**Variables**				
TWD	19.91%	0.000	+0.276IVL_t	-0.248IVN_t	-0.036IMP_t	+0.061EXP_t	-0.254WPI_{t-1}	+0.079GDP_{t-3}	
		(-0.132)	(2.703)	(-3.323)	(-2.785)	(3.227)	(-1.860)	(2.371)	
PEN	16.94%	-0.003	0.37CPI_t	-0.242MON_t	0.035GDP_{t-3}				
		(-1.185)	+(2.582)	(-2.466)	+(1.710)				
INR	18.39%	0.008	+0.188IVL_t	-0.096CPI_t	-0.043GDP_t	-0.544MON_{t-1}			
		(3.028)	(2.380)	(-2.772)	(-2.630)	(-2.883)			
MXN	5.95%	0.010	-0.831WPI_t	-0.132EXP_t					
		(1.747)	(-1.987)	(-1.745)					
ZAR	8.43%	-0.018	+0.231IVL_t	+2.251MON_t					
		(-2.768)	(1.961)	(2.858)					
CZK	13.87%	-0.005	+0.421IVL_t						
		(-1.928)	(3.800)						
ILS	0.00%	0.001							
		(0.692)							
THB	22.05%	0.013	+0.262IVL_t	+0.092EXP_t	-1.176MON_t	-0.235CPI_{t-1}	-0.261GDP_{t-3}		
		(2.255)	(1.662)	(2.584)	(-2.181)	(-1.786)	(-2.694)		
PHP	14.59%	-0.001	-0.242IVN_t	+0.326WPI_{t-1}	+0.015EXP_{t-1}				
		(-0.663)	(-3.372)	(2.881)	(2.187)				
IDR	39.41%	-0.038	+1.487WPI_t	-0.263EXP_t	-1.3WPI_{t-1}	+1.848MON_{t-1}	-0.339GDP_{t-3}		
		(-3.122)	(3.252)	(-1.797)	(-2.435)	(2.750)	(-2.498)		
KRW	14.21%	-0.010	+0.496IVL_t	+0.069GDP_t					
		(-2.631)	(3.421)	(2.006)					
SKK	3.32%	0.008	-0.062IVN_t	-0.068IMP_{t-1}					
		(2.288)	(-2.079)	(-1.775)					
BRL	18.67%	-0.012	+0.245EXP_t	+0.261IMP_{t-1}	-0.237EXP_{t-1}				
		(-1.186)	(2.295)	(2.613)	(-1.722)				
CLP	26.80%	0.035	-0.203IVN_t	+0.498WPI_t	-0.052IMP_t	-0.729MON_t	-0.775CPI_{t-1}	-0.78WPI_{t-1}	-0.066EXP_{t-1}
		(4.494)	(-2.061)	(1.993)	(-1.758)	(-1.678)	(-2.204)	(-3.548)	(-2.527)
COP	2.20%	0.000	+0.071IMP_{t-1}						
		(0.102)	(2.244)						
PLN	2.11%	0.004	-0.383CPI_{t-1}						
		(0.765)	(-1.909)						
TRY	8.69%	0.015	-0.534IVN_t						
		(2.442)	(-2.219)						
HUF	13.94%	0.012	-0.065IVL_t	+0.219IVN_t	-0.804CPI_t	+0.725WPI_{t-1}			
		(1.195)	(-2.789)	(2.158)	(-2.509)	(2.130)			
ARS	41.96%	0.003	-0.566CPI_t	+0.674CPI_{t-1}	-0.132EXP_{t-1}	-1.513MON_{t-1}	+0.102GDP_{t-3}		
		(0.468)	(-5.755)	(6.618)	(-2.268)	(-2.450)	(1.761)		

This panel contains the final models for Support and Resistance returns resulting from the backward elimination procedure described in Section 5.1. *t*-statistics are given in parentheses.

Appendix A3: Pesaran and Timmermann Test

Consider a variable for forecasts, $\hat{y}_t$ and a variable for actual (realized) values, y_t. Let

p = probability (proportion) that the sign of y_t is correctly predicted,
π_1 = Pr(y_t > 0),
π_2 = Pr(y_t > 0),
p_1 = sample proportion of times that y_t is positive
p_2 = sample proportion of times that $\hat{y}_t$ is positive

The null hypothesis is that y_t and y_t are independently distributed of each other. This means that the forecast values have no ability to predict the sign of y_t. Under this null hypothesis, the number of correct sign predictions in the sample is binomially distributed with T trials and probability of success equal to:

$$\pi^* = \pi_1 \pi_2 + (1 - \pi_1)(1 - \pi_2).$$

In case π_1 and π_2 are known, the test statistic is defined as:

$$PTK = \frac{(p - \pi *)}{[\pi *(1 - \pi *)/T]^{1/2}} \quad .$$

In case π_1 and π_2 are unknown, they can be estimated with the sample proportions p_1 and p_2:

$$p^* = p_1 p_2 + (1 - p_1)(1 - p_2).$$

Under the null hypothesis the test statistic now follows asymptotically a standard normal distribution, which is defined as follows:

$$PTNK = \frac{(p - p*)}{[\hat{V}(p) - \hat{V}(p*)]^{1/2}} \xrightarrow{d} N(0,1),$$

where:
$\hat{V}(p) = p^*(1-p^*)/T,$
$\hat{V}(p^*) = (2p_1 - 1)^2 p_2(1-p_2)/\mathrm{T} + (2p_2 - 1)^2 p_1(1-p_1)/\mathrm{T} + 4p_1p_2(1-p_1)(1-p_2)/T^2$

The square of the $PTNK$-statistic is asymptotically equal to the $\chi^2(1)$ statistic.