**Feedback trading in currency markets: international evidence**

Mohammad Tayeha and Vasileios Kallinterakisb

a School of Business, The University of Jordan, Amman 11492, Jordan. Email: [m.tayeh@ju.edu.jo](mailto:m.tayeh@ju.edu.jo)

b University of Liverpool Management School, Chatham Building, Chatham Street, Liverpool L69 7ZH, UK; E-Mail: [hsycui2@liverpool.ac.uk](mailto:hsycui2@liverpool.ac.uk); [V.Kallinterakis@liverpool.ac.uk](mailto:V.Kallinterakis@liverpool.ac.uk)

**Abstract**

We investigate the presence of feedback trading in 66 currencies for the 2001-2018 period and find that feedback traders are active in many of them, giving rise mostly to positive feedback trading, when present. This suggests that feedback traders assume a stabilizing role, buying when currencies depreciate and selling when they appreciate, with depreciations found to boost positive feedback trading more strongly than appreciations. Feedback trading is found to exhibit long memory for most currencies, while no discernible feedback trading patterns surface within-versus-outside the recent global financial crisis.

JEL Classification: G15; G4

Keywords: feedback trading; currencies; long memory

**1. Introduction**

Feedback trading constitutes a rather popular investment practice internationally, with ample evidence confirming its presence in stock exchanges worldwide, mainly for equity indices, but also for derivatives and exchange-traded funds (Koutmos, 2014). An asset class for which relatively little is known about the presence of feedback traders is the currency market; the limited research to date (Aguirre and Saidi, 1999; Laopodis, 2005) by and large suggests that investors feedback trade in many currencies, without, however, exhibiting uniformity or any discernible patterns in their trading conduct. We aim at contributing to that debate by investigating the existence of feedback trading in a large sample (66) of currencies, representing a wide cross section of markets (developed; emerging; frontier) for the 2001-2018 period.

More specifically, our study first examines whether feedback trading is present in the currency market and whether it grows more significant following currency appreciations or depreciations. Second, we test whether feedback trading exhibits long memory in its structure; and third, whether the global financial crisis has culminated in any distinct feedback trading patterns compared to the non-crisis years.

Our results suggest that feedback traders are active in several (though not most) currencies, with positive feedback trading being stronger during currency depreciations (indicating that feedback traders buy currencies following their depreciations, in effect exerting a stabilizing influence). Where feedback trading is present, it is positive feedback trading that surfaces in most cases following both appreciations and depreciations, thus confirming its stabilizing presence; in addition, we produce evidence on feedback trading bearing long memory in its dynamics for the majority of currencies. As regards the global financial crisis, it is found to produce no particular feedback trading patterns compared to non-crisis years (for which no clear patterns emerge either). Overall, our evidence denotes that positive feedback trading is encountered in several currencies internationally, with the most consistent evidence in favor of its presence surfacing for emerging/frontier economies’ currencies.

Our research contributes significantly to extant research in behavioural finance by showcasing that currency markets entail versatile feedback trading dynamics; several currencies present us, for example, with no feedback trading when the latter is estimated unconditionally, only to generate various patterns once feedback trading is conditioned on currency appreciations/depreciations or estimated within-versus-outside the global financial crisis. We further contribute to the debate in behavioural finance about whether less developed markets are more likely to demonstrate noise trading patterns by showing that feedback trading in emerging/frontier market currencies tends to be more robust across various tests.

The rest of this paper is organized as follows: section 2 is devoted to a concise literature review of feedback trading, in terms of both its sources and empirical evidence; section 3 presents the data utilized with descriptive statistics, before outlining the empirical design employed; section 4 presents and discusses the results, while section 5 concludes.

**2. Feedback trading**

The concept of feedback trading constitutes an umbrella term, accommodating all investment strategies relying on historical data (primarily prices and volume) to profit from (actual or perceived) trends in the market and, as such, runs counter to market efficiency (Fama, 1991) *per se* in several ways. First of all, the fact that feedback traders rely on historical prices and not fundamentals, suggests a direct departure from the rationality assumption of the efficient markets’ hypothesis. Second, the sheer fact that feedback traders utilize historical prices in their strategies is in contrast to the weak form of market efficiency, according to which, all historical information has already been incorporated in past prices, thus suggesting that extrapolating from the latter cannot yield any extra profits. Third, the fact that feedback traders aim at exploiting actual or perceived trends suggests that, in their attempt to ride on (or buck) those trends, they are conducive to amplifying serial correlation in securities’ returns (Cutler et al., 1990); if this persists for prolonged periods of time, it may well lead securities’ returns to deviate from their fundamental values (De Long et al., 1990) and exhibit excess volatility (Farmer, 2002).

Contingent on their directional response to trends, feedback traders are classed either as *positive* or *negative* ones. Positive feedback traders aim at tracking price-trends, i.e. buy when prices rise and sell when they fall, in effect, trend chasing. Perhaps the best-known expression of positive feedback trading are momentum strategies (Jegadeesh and Titman, 2001), which involve going long on recent winners and short on recent losers in the short-to-medium run. On the other hand, negative feedback traders aim at bucking existing price-trends, i.e. sell when prices rise and buy when they fall; this is a clear manifestation of contrarian trading, whose profitability has been confirmed over time (see e.g. Galariotis, 2014).

With regards to the factors motivating feedback trading there exists a notable wealth of argumentation. To begin with, feedback trading can be driven by *observational learning* (Holmes and Kallinterakis, 2014); the latter hinges on the fact that stock prices offer investors a noisy (and low-cost) summary gauge of aggregate market activity. Uninformed investors bear a natural tendency to monitor their better-informed counterparts in order to free-ride on their information; however, the issue they are being faced with is that this monitoring comes at a cost, which they may not be willing to shoulder (uninformed traders, being unsophisticated, are not expected to be in command of adequate resources for such a task). Monitoring stock prices, on the other hand, alleviates this process, as it allows uninformed investors the opportunity of tracking the aggregate trading in the market at no cost, without having to monitor the trades of other investors individually.

Investors may also resort to feedback trading in order to use past prices as a means of tackling *information risk*. Small capitalization stocks, for example, enjoy limited analysts’ following, the result being that they are typified by high information risk. An investor wishing to trade such a stock will find it hard to obtain information and may decide to rely on the stock’s price-history as a substitute for information (see e.g. Lakonishok et al., 1992; Wermers, 1999; Sias, 2004). Similarly, investors focusing on overseas markets may also consider themselves informationally disadvantaged vis-à-vis these markets’ domestic investors and may also, therefore, view feedback trading as a viable option (Brennan and Cao, 1997; Kang and Stulz, 1997; Choe et al., 1999; Dahlquist and Robertsson, 2001; Froot et al., 2001; Kim and Wei, 2002a; b; Kalev et al., 2008; Lin and Swanson, 2008).

*Rational speculation* can also give rise to feedback trading, if rational investors believe that exploiting their noise counterparts is profitable, irrespective of prices deviating from fundamental value. This possibility was described by Soros (1987) and modelled analytically by De Long et al. (1990), Farmer (2002) and Farmer and Joshi (2002); in essence, it involves a model-setting whereby informed investors (who know what an asset’s fundamental value is at any point in time) interact with uninformed investors (who ignore fundamentals and can only observe an asset’s price-history). The crux of those studies is that rational investors will prefer to trade ahead of uninformed investors before information signals hit the market, in anticipation of uninformed investors’ (positive for “good” and negative for “bad” signals) response to those signals. If, for example, the signal is “good”, rational investors will buy ahead of the signal’s arrival, push the price upward, then wait for noise traders to assume an uptrend is at works and start buying as well, thus pushing the price even higher. Upon the signal’s arrival, rational investors may well choose to both sell (the price by now may well have crossed fundamental value due to noise traders’ purchases) and sell short (they know that as soon as they start selling, the price will start falling, prompting noise traders to perceive a downtrend and start selling as well, depressing the price even more - in which case selling short will yield a profit for rational investors). As a result, rational speculation involves informed investors exploiting their informational superiority by launching trends well ahead of news’ arrival, in anticipation of noise traders’ response; such behaviour obviously forces prices to deviate from their intrinsic value and can boost trends and serial correlation in securities’ returns.

*Style investing*, a very popular investment practice (particularly among institutional investors; see e.g. Bennett et al., 2003) can also give rise to feedback trading; known also as “characteristic trading”, it involves any strategy selecting stocks on the premises of specific characteristics, related e.g. to past performance, value, size, or sector, to mention a few. Styles based on historical prices, such as, for instance, momentum and contrarian, naturally promote feedback trading, as they are aiming at exploiting trend continuations (momentum) and reversals (contrarian). What is more, technical analysis, perhaps the oldest group of trading styles known to date, is further capable of fomenting feedback trading, since its trading rules are, by definition, price-based (Lo et al., 2001; Nazário et al., 2017).

Feedback trading is also promoted by investment professionals’ reputational/career considerations. Evidence (Grinblatt et al., 1995; Holmes et al., 2013) suggests that fund managers are particularly prone to *window dressing* as a practice, the latter involving adding recent winners in their portfolio and disposing of recent losers, in order to generate the impression of possessing good quality stock-picking skills. If so, this is expected to boost momentum trading across fund managers’ ranks, thus amplifying positive feedback trading in the market.

Several *trading schemes* primarily encountered in the institutional segment of equity markets have also been found to promote feedback trading in capital markets internationally. Such practices include stop-loss and take-profit orders (Osler, 2005), margin trading (Watanabe, 2002; Hirose et al., 2009) and portfolio insurance (Grossman and Zhou, 1996; Kodres, 1994) and are activated contingent on prices reaching a particular threshold; in the case of stop-loss orders, for example, a slump in price below a predetermined threshold will trigger the sale of stocks, in order for the trader to avoid the further loss of wealth in case of the slump’s prolonging (for more on how similar strategies foment feedback trading, see Balduzzi et al., 1995).

Finally, it would be appropriate to include *intraday trading* as a key factor fostering feedback trading in contemporary financial markets. Whether it pertains to speculative retail investors day-trading (e.g. Barber et al., 2014) or institutional investors employing algorithmic and high-frequency trading (Andrikopoulos et al., 2017), the fact remains that intraday trading strategies are price-based[[1]](#footnote-1), geared towards exploiting within-session price-changes (often at intervals as minuscule as a few milliseconds) and, as such, also help accentuate feedback trading dynamics.

Empirically, feedback trading has been documented both at the micro level (i.e. from studies based on investors’ transactions/portfolios) and the macro level (i.e. from studies based on market prices). At the micro level, evidence (Lakonishok et al., 1992; Grinblatt et al., 1995; Nofsinger and Sias, 1999; Wermers, 1999; Chan et al., 2002; Sias, 2004; Froot and Teo, 2008; Lin and Swanson, 2008; Choi and Sias, 2009; Celiker et al., 2015; Frijns et al., 2016) suggests that US institutional investors are prone to positive feedback trading in their domestic equity trades (more strongly so during recent decades), with similar results being reported regarding their trading patterns in overseas markets (Brennan and Cao, 1997; Kaminsky et al., 2004) and when trading American Depositary Receipts (Li and Yung, 2004). In the most comprehensive cross-market study to date, Choi and Skiba (2015) showed that mutual funds positive feedback traded in most international markets during the 1999-2010 window; in terms of single-market studies, evidence of significant feedback trading of either sign for fund managers has been reported for Finland (Do et al., 2008; Grinblatt and Keloharju, 2000), Germany (Walter and Weber, 2006; Kremer and Nautz, 2013), India (Tayde and Rao, 2011), Poland (Voronkova and Bohl, 2005), South Korea (Choe et al., 2005; Choe et al., 1999; Kim and Wei, 2002a; b; Jeon and Moffett, 2010), Taiwan (Yang, 2002; Hung et al., 2010; Chen et al., 2012), and the UK (Wylie, 2005; Blake et al., 2017). What is more, retail investors have also been found to be susceptible to (positive and negative) feedback trading patterns in Australia (Colwell et al., 2008), Finland (Do et al., 2008; Grinblatt and Keloharju, 2000) and Germany (Dorn et al., 2008), with no evidence of feedback trading surfacing among Chinese retail investors (Feng and Seasholes, 2004).

Turning now to the macro level, research suggests the presence – to varying degrees - of (predominantly positive) feedback trading internationally for various asset classes, including equity indices (Sentana and Wadhwani, 1992; Koutmos, 1997; Koutmos and Saidi, 2001; Watanabe, 2002; Bohl and Reitz, 2004; 2006; Bohl and Siklos, 2005; 2008; Koutmos, 2006; Schuppli and Bohl, 2010; Antoniou and Koutmos, 2014; Chau and Deesomsak, 2015; Kuttu and Bokpin, 2017), fixed-income (Cohen and Shin, 2002), futures (Antoniou et al., 2005, Chau et al., 2008; Kurov, 2008; Antoniou et al., 2011), exchange-traded funds (Chau et al., 2011; Kallinterakis and Kaur, 2011; Charteris et al., 2014) and – of direct interest to this study – currencies (Aguirre and Saidi, 1999; Laopodis, 2005).

**3. Data and Methodology**

**3.1 Data**

Our sample includes 66 currencies from various markets (developed, emerging and frontier) and spans the 29/12/2000 – 31/5/2018 period. We collected data on their daily closing spot prices (with respect to the US dollar)[[2]](#footnote-2) from the Thomson-Reuters Datastream database. Table 1 presents a series of descriptive statistics for our currencies’ log-differenced returns (calculated as the first difference between a currency’s logarithmic value on day *t* and its logarithmic value on day *t-1*). The performance of our currencies is rather mixed, with 36 (30) of the currencies exhibiting a positive (negative) average return[[3]](#footnote-3) overall during the sample period. The currencies’ returns assume a rather wide range of values, with the maximum daily return observed for the Ukrainian Hryvnia (approximately 21.4%) and the minimum daily return identified with the Egyptian Pound (approximately -54%). All currencies exhibit significant and high excess kurtosis, indicating significant departures from normality, something further confirmed via the uniformly significant Jarque-Bera test statistics. Most currencies (58) also exhibit significant skewness, which is relatively evenly split into positive and negative among them.

[Insert Table 1]

**3.2 Methodology**

Our empirical design hinges on the model proposed by Sentana and Wadhwani (1992), which assumes a market setting with two interacting trader-types, rational speculators and feedback traders; as per rational speculators, their demand function is founded on a mean-variance framework, as follows:

(1)

In the above equation, Q represents the fraction of the currency’s market held by rational speculators, Et-1(Rt) denotes the expectation of the currency’s return in period *t* as of period *t-1*, *α* is the rate of return of risk-free investments, is the coefficient of risk aversion and represents the conditional variance (i.e. volatility) of the currency. What the above equation suggests is that the demand for a currency will be a straight function of its expected return (the “Et-1(Rt) – *α”* part) and an inverse function of risk ().

Feedback traders rely on historical price series; in the context of the Sentana and Wadhwani (1992) model they are assumed to base their contemporaneous trades on one-lag (i.e. previous day) returns as follows:

(2)

In the above equation, if the feedback coefficient (γ) is positive (negative), this will suggest the presence of positive (negative) feedback trading. Positive feedback traders buy (sell) following a currency’s depreciation (appreciation) – and vice versa for negative feedback traders (Laopodis, 2005).[[4]](#footnote-4),[[5]](#footnote-5)

In equilibrium, Qt + Yt = 1, hence:

(3)

Converting Equation (3) in regression form (by setting Rt = Et-1(Rt) + ut) we obtain:

(4)

Equation (4) demonstrates that the first-order return-autocorrelation is a straight function of risk, since, the larger the , the larger the autocorrelation grows. What the sign of this autocorrelation will be depends on the sign of feedback trading; if γ >0 (γ <0), then the first-order return-autocorrelation will be negative (positive). However, the γ-coefficient may be capturing the effects of both feedback trading as well as market frictions (such as thin trading, which, by definition, enhances autocorrelation in returns; see Antoniou et al., 1997). To distinguish between these two possibilities, Equation (4) is re-arranged as follows:

(5)

Here, ϕ0 is the constant part of autocorrelation, reflective of the effects of market frictions, such as thin trading; on the other hand, ϕ1 is the feedback trading coefficient. Since ϕ1 = - κγ, ϕ1 > 0 (ϕ1 < 0) would suggest the presence of negative (positive) feedback traders.

To assess whether positive feedback trading is asymmetric between currency appreciations and depreciations, we employ the following empirical specification:

(6)

In Equation (6), the coefficient of equals:

+

(7)

-

A significantly positive value for would suggest that positive feedback trading is more pronounced during currency appreciations, compared to currency depreciations.[[6]](#footnote-6)

To test for the possibility that feedback trading varies with the sign of the exchange rate change (i.e. appreciation/depreciation), we employ the following empirical specification:

(8)

Here, the dummy Dt-1 assumes the value of unity in case the currency has appreciated, zero in case it has depreciated. The *t-1* in the subscript of the dummy is used here due to the fact that our feedback traders trade based on lagged currency returns and, hence, they would condition their trades upon the depreciation or appreciation of a currency one day back. The interpretation of the coefficients here is identical to that of Equation (5).

We then test whether feedback trading in the currency market has a memory longer than that suggested by the Sentana and Wadhwani (1992) model (which assumes that feedback traders base their trading on a single lag of returns). To that end, we assume that feedback traders base their trades on n return-lags (n = 2, 3, 4 …) and re-estimate Equation (5) for each of those lag-lengths incorporated in Equation (2). For each currency, the optimal lag-length is then inferred via a grid-search, by identifying the number of lags that produces the maximum value of the likelihood function.[[7]](#footnote-7)

We finally test whether the outbreak of the global financial crisis in 2007-2008 has produced any effect over the presence of feedback trading in the currency market; to that end, we employ the following specification:

(9)

The dummy variable Dt here is equal to one for the 10/10/2007 – 6/3/2009 period, zero otherwise. The choice of the crisis-period is motivated by the fact that the US market began its descending course in October 2007 (on October 9th, 2007 the Dow Jones Industrial Average index realized its peak value - 14,164.53 units), following which the crisis started becoming more evident in the US and internationally, with the DJIA index bottoming out on the 6th of March, 2009.

The estimation of the above models pre-supposes the identification of the conditional variance specification ( needs to be defined); for this purpose, we select the asymmetric GARCH model (Glosten et al., 1993):

(10)

The rationale underlying our choice hinges on the fact that said specification is *ad hoc* designated to capture the well-documented leverage-effect in volatility, according to which the latter increases relatively more following negative shocks as opposed to positive ones of the same magnitude. In the above equation, is a dummy equal to one if the lagged shockis negative, zero otherwise; if volatility is asymmetric (i.e. if the leverage effect is present in volatility), this will be reflected in a significantly positive .

**4. Results - Discussion**

Table 2 presents the results from the estimations of Equations (5) & (10); as the -estimates indicate, most currencies (38) exhibit no first-order autocorrelation in their return-series, with 10 (18) entailing significantly[[8]](#footnote-8) positive (negative) autocorrelation. It is, perhaps, worth noting here that almost all of those 28 currencies with significant autocorrelation belong to emerging/frontier economies (with the exception of the Norwegian Krone and the Swiss Franc), thus denoting that emerging/frontier markets’ currencies are more likely to accommodate frictions in their return-generation process compared to developed market ones. It is possible that these frictions hail from the lower volumes that these currencies enjoy in the foreign exchange market, leading their rates to exhibit greater staleness (which increases their autocorrelation)[[9]](#footnote-9) compared to those of developed markets.

[Insert Table 2]

With regards to feedback trading, the coefficient is significant in 20 cases, indicating that feedback trading does not dominate international currency markets. Of the 20 cases, 14 involve positive ( <0) and 6 involve negative ( >0) feedback trading; as a result, most feedback trading in currency markets tends to be stabilizing (since positive feedback traders buy when currencies depreciate and sell when they appreciate). The positive feedback trading observed in those 14 currencies may be the result of their central banks’ interventions, buying to support their currencies in case of depreciations and selling to stabilize them in case of appreciations (Laopodis, 2005). Risk aversion is also a possibility here, with positive feedback traders selling in view of currency appreciations to shield themselves against the possibility of these appreciations being short-lived (perhaps due to anticipated intervention by central banks, as mentioned previously) and, thus not credible (Aguirre and Saidi, 1999). With regards to the 6 currencies where negative feedback trading is present, it is possible that this is due to feedback traders selling (buying) when these currencies depreciate (appreciate) in order to exit (enter) before the currencies lose (gain) more value. Such strategies are motivated by profit-taking incentives and risk aversion: if negative feedback traders sell depreciating currencies, it may well be because they believe that they will continue to lose value and, hence, wish to reduce their exposure to them; on the other hand, negative feedback traders buy appreciating currencies because they believe they will continue to appreciate in value and, thus choose to buy them early on, before they become more expensive. Again here, we notice that the presence of feedback trading[[10]](#footnote-10) is mainly associated with emerging/frontier market currencies (with the exceptions of the Japanese Yen, the Norwegian Krone and the UK Pound), in line with the results reported by Aguirre and Saidi (1999).[[11]](#footnote-11)

As far as the volatility structure of our sample currencies is concerned, volatility is persistent ( is significant) in almost all of them (with the exceptions of the Argentine Peso and the Egyptian Pound), with news having a positive impact over it (as the significantly positive -values indicate for most - 58 - currencies). Evidence of asymmetric volatility (reflected through a significantly positive ) is documented for just under half (32) of the 66 currencies of our sample.

Table 3 presents the estimates from the set of Equations (6) & (10), which are employed to test for directional asymmetry in positive feedback trading (i.e. whether the latter is stronger during currency appreciations or depreciations). As the results in the table show, the presence of significant first-order autocorrelation is confirmed for 30 currencies, 18 of which entail negative and the rest 12 positive autocorrelation, similar to the estimates for  presented in Table 2. Again here, with the exception of the Norwegian Krone, significant autocorrelation is detected in currencies from emerging/frontier economies. Feedback trading appears significant for only 16 currencies (compared to 20 in Table 2), with being significantly negative (positive) in 13 (3) cases, suggesting that it is positive feedback trading that is more

[Insert Table 3]

likely to be encountered in currencies with significant feedback traders’ presence. With the exception of the Japanese Yen and the Norwegian Krone, the rest of the 14 currencies with significant feedback trading belong to emerging/frontier economies, thus confirming the previous results from Table 2 on those economies’ currencies being more susceptible to feedback trading. With respect to the -coefficient, it is interesting to note that its values appear significant in 20 currencies, with 19 of those values being negative. As mentioned in the previous section, significantly positive values of that coefficient would denote that positive feedback trading is stronger during currency appreciations; however, this seems to be the case with the Fijian Dollar alone in our results. The significantly negative -values in 19 currencies suggest that positive feedback trading is stronger during currency depreciations, namely that feedback traders tend to buy when currencies depreciate. Unlike Table 2 where feedback trading was confined almost exclusively to emerging/frontier markets’ currencies, is significantly negative for 13 emerging/frontier and 6 developed markets’ currencies, thus indicating that controlling for appreciations/depreciations allows us additional insight into the feedback trading dynamics of currency markets that could not be captured testing for feedback trading unconditionally. In several (12) cases, we also notice that there exist currencies with insignificant - yet significantly negative -values. This may be the result of strongly countervailing positive and negative feedback trading dynamics, whose interaction yields insignificant feedback trading in the aggregate (and, hence, insignificant -values).[[12]](#footnote-12) In those currencies, is significantly negative, because depreciations prompt stronger positive feedback trading, possibly due to the stabilizing role of central banks’ intervention (i.e. via purchases of their currency) when their currency depreciates.[[13]](#footnote-13) With regards to the volatility dynamics, these appear qualitatively similar to those from Table 2, confirming that volatility among currencies is persistent, responds significantly to news, yet not asymmetrically so, in most cases.[[14]](#footnote-14)

Table 4 presents the first-order autocorrelation and feedback estimates from Equations (8) and (10), where we assess whether it is currency appreciations or depreciations that motivate feedback trading in currencies. A particularly interesting finding is that most (36) of our sample currencies exhibit no feedback trading whatsoever following appreciations or depreciations. A further twelve currencies present us with significant feedback trading of either sign following both appreciations and depreciations, while feedback trading is significant for thirteen (five) currencies following appreciations (depreciations). The vast majority of feedback trading significance is associated with positive feedback trading, indicating that, in most cases, feedback traders tend to buy (sell) following depreciations (appreciations).[[15]](#footnote-15)

We now assess how feedback trading manifests itself when feedback traders rely on n return-lags, longer than a single day (n = 2, 3, 4 …); as mentioned in the previous section, this merits incorporating each of those lag-lengths in Equation (2) in turn and re-estimating Equation (5). For each currency, the optimal lag-length is then inferred via a grid-search, by identifying the number of lags that produces the maximum value of the likelihood function. As the estimates outlined in Table 5 showcase, the majority (46) of our sample currencies entail significant feedback trading for higher lags; with the exception of four currencies for which negative feedback trading is observed, the rest 40 currencies accommodate positive feedback trading. The optimal number of lags ranges from two to six, with most currencies exhibiting feedback trading for lag-lengths of two to four lags.[[16]](#footnote-16) These results suggest that the tendency of feedback traders to buy (sell) currencies that depreciate (appreciate) is much stronger when relying on longer lags, compared to when relying on a single lag (for which feedback trading was reported present in 20 currencies; see Table 2). It is possible that this is due to currency traders relying on technical trading rules of horizons longer than a single day, something implied in Shiller (1990) and Osler (2005). A simple example here would be that of an investor trading based on an empirical regularity she has discovered for longer lags of a currency’s returns (e.g. that a currency exhibits strong second- or third-order autocorrelation) or using a short moving average of 2-4 days’ length (in which case, her trades would involve anchoring on returns beyond those of the first lag).

We finally turn to examine whether the outbreak of the global financial crisis (2007-2009) has produced any effect over the observed feedback trading in our sample currencies. Table 6 presents the autocorrelation and feedback estimates from Equations (9) and (10) and we notice, at first glance, that 24 currencies entail no feedback trading, be it within or outside said crisis. Feedback trading is significant both within and outside the crisis for 12 currencies (without any sign-pattern emerging, however); it is also present for 15 currencies during the crisis only and for 15 currencies outside the crisis only. Positive feedback trading dominates both inside and outside the crisis, while negative feedback trading appears mainly during the crisis compared to outside it. The above suggest that the crisis did not generate any discernible effect over feedback trading in our sample currencies; where present, feedback traders mostly resorted to buying when currencies depreciated and selling when they appreciated, thus overall, conferring a stabilizing influence over them.[[17]](#footnote-17)

[Insert Table 4]

[Insert Table 5]

[Insert Table 6]

**5. Conclusion**

This study investigated whether feedback traders are active in the currency market, an asset class for which relatively little is known to date as regards the presence of feedback trading. Drawing on a wide cross section of 66 currencies for the 2001 – 2018 window, we present evidence confirming the existence of significant feedback trading for several of our sample currencies; for the most part, this refers to positive feedback trading, thus suggesting that feedback traders, when present, tend to stabilize the currency market by buying (selling) when currencies depreciate (appreciate). This is confirmed when conditioning feedback trading on lagged appreciations/depreciations, while further tests on the directional asymmetry of feedback trading indicate that investors positive feedback trade more following currency depreciations, thus denoting that such behaviour is mainly associated with currency purchases when currencies have lost value. Additional tests reveal that feedback trading bears long memory, with the majority of currencies entailing significant (and mostly positive) feedback trading for multiple lags in the return-generation process. What is more, the outbreak of the global financial crisis appears to generate no discernible feedback trading patterns across our sample currencies, while also confirming the prevalence of positive feedback trading (whenever feedback trading is present). Key to our results, however, is the fact that the vast majority of feedback trading is detected among emerging/frontier economies’ currencies, with very few developed economies’ ones producing consistent evidence of feedback trading across our tests.

Our results bear important implications for the investment community, as they suggest that feedback trading is present in several currencies internationally and should thus be considered when devising trading strategies for this asset class, particularly for emerging/frontier economies’ currencies, where feedback trading is stronger. The presence of feedback trading suggests that price-based trading strategies (in effect, feedback-style ones) would be useful when trading many currencies, in order to possibly exploit the feedback trading present in the latter. Further to that, the fact that a large number of our sample currencies is found to entail significant return-autocorrelation denotes that many currencies are characterized by inefficiencies – which, again, can be profitably exploited via *ad hoc* strategies of a feedback nature. The fact that the vast majority of currencies with feedback trading present belong to emerging/frontier economies indicates that these countries’ monetary authorities should be monitoring their currencies’ movements closely, in order to intervene on time and avoid potential destabilizing effects (in case, for example, feedback traders lead to wild swings of exchange rates). Future research could also consider assessing the presence of feedback trading in the currency market at the micro level (i.e. using investors’ transaction data) in order to gauge whether and how feedback trading evolves real-time and whether it is initiated during specific trading times and by specific trade-types (as this might be indicative of which investor-types motivate it).

**References**

Aguirre, M. S., & Saidi, R. (1999). Feedback trading in exchange-rate markets: evidence from within and across economic blocks. *Journal of Economics and Finance*, 23(1), 1-14.

Andrikopoulos, P., Kallinterakis, V., Leite Ferreira, M. P., and Verousis, T. (2017). Intraday Herding on a Cross-Border Exchange, *International Review of Financial Analysis*, Vol. 53, pp. 25-36.

Antoniou, A., N. Ergul and P.R. Holmes (1997), ‘Market Efficiency, Thin Trading and Nonlinear Behaviour: Evidence from an Emerging Market’, *European Financial Management*, 3(2): 175–90.

Antoniou, A. and Koutmos G. (2014). The cost of credit and positive feedback trading: title evidence from the UK stock market. *Journal of Applied Finance and Banking*, 4:2, 21-32.

Antoniou, A., Koutmos, G., & Pericli, A. (2005). Index futures and positive feedback trading: evidence from major stock exchanges. *Journal of Empirical Finance*, 12(2), 219-238.

Antoniou, A., Koutmos, G. and Pescetto, G. (2011), “Positive feedback trading: evidence from futures markets”, *Global Business and Economics Review*, Vol. 13, No. 1, pp. 13-25.

Balduzzi, P., Bertola, G., & Foresi, S. (1995). Asset price dynamics and infrequent feedback trades. *Journal of Finance*, 50:5, 1747-1766.

Barber, B., Lee, Y.T., Liu, Y.J. & Odean, T. (2014). The cross-section of speculator skill: Evidence from day trading. *Journal of Financial Markets*, 18, 1-24.

Bennett, J. R., Sias, R., & Starks, L. (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies*, 16, 1203-1238.

Blake, D, Sarno, L, & Zinna, G. (2017). The market for lemmings: the herding behavior of pension funds. *Journal of Financial Markets*, 36, 17-39.

Bohl, M. T. & Reitz, S, 2004, “The Influence of Positive Feedback Trading on Return Autocorrelation: Evidence from the German Stock Market”, in: Stephan Geberl, Hans-Rüdiger Kaufmann, Marco Menichetti und Daniel F. Wiesner (Hrsg.), Aktuelle Entwicklungen im Finanzdienstleistungsbereich, Physica-Verlag, Heidelberg, 221 - 233.

Bohl, M. T. & Reitz, S. ,2006, “Do Positive Feedback Traders Act in Germany’s Neuer Markt?”, *Quarterly Journal of Business and Economics*, Volume 45, Nos. 1 and 2.

Bohl, M. T. and Siklos, P. L., 2005, “**Trading Behavior During Stock Market Downturns: The Dow, 1915 – 2004”**, Working Paper, European University Viadrina Frankfurt (Oder).

Bohl, M. T., & Siklos, P. L. (2008). **Empirical evidence on feedback trading in mature and emerging stock markets.** *Applied Financial Economics*, 18-17, 1379-1389.

Brennan, M.J., & Cao, H. (1997). International portfolio investment flows. *Journal of Finance*, 52(5), 1851-1880.

Campbell, J.Y., Grossman, S.J. and Wang, J. (1993). Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics*, 108:4, 905-939.

Celiker, U., Chowdhury, J. and Sonaer, G. (2015). Do mutual funds herd in industries? *Journal of Banking and Finance*, 52, 1-16.

Chan, L.K.C., Chen, H-L and Lakoniskok, J. (2002). On mutual fund investment styles. *Review of Financial Studies*, 15:5, 1407-1437.

Charteris, A., Chau, F., Gavriilidis, K., & Kallinterakis, V. (2014). Premiums, discounts and feedback trading: evidence from emerging markets' ETFs. *International Review of Financial Analysis*, 35, 80-89.

Chau, F., & Deesomsak, R. (2015). Business cycle variation in positive feedback trading: evidence from the G-7 economies. *Journal of International Financial Markets, Institutions and Money*, 35, 147-159.

Chau, F., Deesomsak, R., & Lau, M. (2011). Investor sentiment and feedback trading: evidence from the exchange traded funds market. *International Review of Financial Analysis*, 20, 292-305.

Chau, F., Holmes, P., & Paudyal, K. (2008). The impact of universal stock futures on feedback trading and volatility dynamics. *Journal of Business Accounting and Finance*, 35, 227-249.

Chen, Y.F., Yang, S.Y., Lin, F.L., 2012. Foreign institutional industrial herding in Taiwan stock market. *Managerial Finance* 38 (3), 325–340.

Choe, H., Kho, B. C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics*, 54, 227-264.

Choe, H., Kho, B. C., & Stulz, R. M. (2005). Review of Financial Studies, 18:3, 795-829.

Choi, N., & Sias, R. W. (2009). Institutional industry herding. *Journal of Financial Economics*, 94, 469-491.

Choi, N., & Skiba, H. (2015). Institutional herding in international markets. *Journal of Banking and Finance*, 55, 246-259.

Cohen B, Shin H. 2003. Positive feedback trading under stress: evidence from the US Treasury securities market. Working Paper, London School of Economics.

Colwell, D., Henker, J. & Walter, T.S. (2008). Effect of investor category trading imbalances on stock returns. *International Review of Finance*, 8 (3-4), 179-206.

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1990). Speculative dynamics and the role of feedback traders. *American Economic Review*, 80, 63-68.

Dahlquist, M., & Robertsson, G. (2001). Direct foreign ownership, institutional investors, and firm characteristics. *Journal of Financial Economics*, 59, 413−440.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45(2), 379-395.

Do, V., M.G. Tan and J. Westerholm (2008), ‘Correlated Trading in Concentrated Market’, *Journal of International Finance and Economics*, Vol. 8, No. 4, pp. 148-163.

Dorn, D., Huberman, G., & Sengmueller, P. (2008). Correlated trading and returns. *Journal of Finance*, 63, 885-920.

Fama, E. F. (1991). Efficient Capital Markets II. *Journal of Finance*, 46, 1575–1643.

Farmer, J. D. (2002). Market force, ecology and evolution. *Industrial and Corporate Change*, 11(5), 895-953.

Farmer, J. D., & Joshi, S. (2002). The price dynamics of common trading strategies. *Journal of Economic Behavior and Organization*, 49(2), 149-171.

Feng, L., & Seasholes, M. S. (2004). Correlated trading and location. *Journal of Finance*, 59(5), 2117-2144.

Frijns, B., Huynh, T. D., Tourani-Rad, A., & Westerholm, P.J. (2016). Institutional trading and asset pricing. *Journal of Banking and Finance*, 89, 59-77.

Froot, K., O’Connell, P., & Seasholes, M. (2001). The portfolio flows of international investors. *Journal of Financial Economics*, *59*, 151–193.

Froot, K., & Teo, M. (2008). Style investing and institutional investors. *Journal of Financial and Quantitative Analysis*, 43(4), 883-906.

Galariotis, E. (2014). Contrarian and momentum trading: a review of the literature. *Review of Behavioral Finance*, 6(1), 63-82.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48 (5), 1779-1801.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor-types: A study of Finland's unique data set. *Journal of Financial Economics*, 55, 43−67.

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behaviour. *American Economic Review*, 85, 1088-1105.

Grossman, S. J., & Zhou Z. (1996). Equilibrium analysis of portfolio insurance. *Journal of Finance*, 51:4, 1379-1403.

Hasbrouck, J. & Saar, G. (2013). Low Latency Trading. *Journal of Financial Markets*, 16, 646-679.

Hirose, T., Kato, H. K., & Bremer, M. (2009). Can margin traders predict future stock returns in Japan? *Pacific-Basin Finance Journal*, 17, 41-57.

Holmes, P. R., & Kallinterakis, V. (2014). Feedback Trading. In K. Paudyal (Ed.) *Wiley Encyclopedia of Management, Volume 4 (Finance)*, 3rd Edition John Wiley & Sons, Ltd: Oxford, UK.

Holmes, P.R., Kallinterakis, V., Leite-Ferreira, M.P. (2013). Herding in a concentrated market: A question of intent. *European Financial Management*, 19, 497-520.

Hung, W., Lu, C.-C., & Lee, C. F. (2010). Mutual fund herding and its impact on stock returns: evidence from the Taiwan stock market. *Pacific-Basin Finance Journal*, 18, 477-493.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance*, 56(2), 699-720.

Jeon, J.Q., & Moffett, C.M. (2010). Herding by foreign investors and emerging equity market returns: evidence from Korea. *International Review of Economics and Finance*, 19, 698-710.

Kalev, P. S., Nguyen, A.H. & Oh, N.Y. (2008). Foreign versus local investors: Who know more? Who makes more? *Journal of Banking and Finance*, 32, 2376-2389.

Kallinterakis, V. and Kaur, S. (2010), “On the impact of exchange-traded funds over noise trading: evidence from European stock exchanges”, in Gregoriou, G.N., (Eds), *Handbook of Trading*, McGraw-Hill, Europe, pp. 199-212.

Kaminsky, G., Lyons, R.K. & Schmukler, S.L. (2004). Managers, investors, and crises: mutual fund strategies in emerging markets. *Journal of International Economics*, 64, 113-134.

Kang, J., & Stulz, R. M. (1997). Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan, *Journal of Financial Economics*, 46, 3−28.

Kim, W., & Wei, S.-J. (2002a). Offshore investment funds: monsters in emerging markets? *Journal of Development Economics*, 68(1), 205-224.

Kim, W., & Wei, S.-J. (2002b). Foreign portfolio investors before and during a crisis. *Journal of International Economics*, 56(1), 77-96.

# Kmenta, J. (1986). Elements of Econometrics, 2nd ed. McMillan Publishing Co.

# Kodres, L. E. (1994). The existence and impact of destabilizing positive feedback traders: evidence from the S&P 500 index futures market. *Working Paper, Board of Governors of the Federal Reserve System*.

Koutmos, G. (1997). Feedback trading and the autocorrelation pattern of stock returns: further empirical evidence. *Journal of International Money and Finance*, 16(4), 625-636.

Koutmos, D. (2012). An intertemporal capital asset pricing model with heterogeneous expectations, *Journal of International Financial Markets, Institutions and Money*, 22, 1176-1187.

Koutmos, G., 2014, Positive Feedback Trading: A Review, *Review of Behavioral Finance*, 6 (2), 155-162.

Koutmos, G., Pericli, A., & Trigeorgis, L. (2006). Short-term dynamics in the Cyprus stock exchange. *European Journal of Finance*, 12(3), 205-216.

Koutmos, G., & Saidi, R. (2001). Positive feedback trading in emerging capital markets. *Applied Financial Economics*, 11, 291-297.

Kremer, S., & Nautz, D. (2013). Causes and consequences of short-term institutional herding. *Journal of Banking and Finance*, 37, 1676-1686.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review*, 43, 107–127.

Kuttu, S. and Bokpin, G.A. (2017). Feedback trading and autocorrelation patterns in Sub-Saharan African equity markets. *Emerging Markets Finance and Trade*, 53:1, 213-225.

Lakonishok, J., Shleifer, A., & Vishny, R. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32, 23-43.

Laopodis, N. T. (2005). Feedback trading and autocorrelation interactions in the foreign exchange market: further evidence. *Economic Modelling*, 22, 811-827.

Li, D.D., & Yung, K. (2004) Institutional herding in the ADR market. *Review of Quantitative Finance and Accounting*. 23, 5–17.

Lin, Y. A., & Swanson, P. E. (2008). Foreigners’ perceptions of US markets: do foreigners exhibit herding tendencies? *Journal of Economics and Business*, 60, 179-203.

Lo, A.W., Mamaysky, H. and Wang, J. (2000). “Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation”, *Journal of Finance*, Vol. LV (4), pp. 1705-1765.

Nazário, R. T. F., Silva, J. L. e., Sobreiroa, V. A. & Kimuraa, H., 2017. A literature review of technical analysis on stock markets. *The Quarterly Review of Economics and Finance,* 66(2017), pp. 115-126.

Nofsinger, J., & Sias, R. (1999). Herding and feedback trading by institutional and individual investors. *Journal of Finance*, 45(6), 2263-2295.

Osler, C. L. (2005). Stop-loss orders and price cascades in currency markets. *Journal of International Money and Finance*, 24, 219-241*.*

Schuppli, M., & Bohl, M. T. (2010). Do foreign institutional investors destabilize China’s A-share markets? *Journal of International Financial Markets, Institutions and Money*, 20, 36-50.

Sentana, E., & Wadhwani, S. (1992). Feedback traders and stock return autocorrelations: evidence from a century of daily data. *The Economic Journal*, 102 (411), 415-425.

Shiller, R.J. (1990). Market volatility and investor behavior. American Economic Association, Papers and Proceedings, 80:2, 58–62.

Sias, R. W. (2004). Institutional herding. *Review of Financial Studies*, 17, 165-206.

Soros, G. (1987), *The Alchemy of Finance*. New York: John Wiley and Sons.

Mangesh Tayde, S.V.D. Nageswara Rao, (2011),"Do Foreign Institutional Investors (FIIs) Exhibit Herding and Positive Feedback Trading in Indian Stock Markets?", Narjess Boubakri, Jean-Claude Cosset, in (ed.) Institutional Investors in Global Capital Markets (International Finance Review, Volume 12), Emerald Group Publishing Limited, pp. 169 – 185.

Voronkova, S., & Bohl, M.T. (2005). Institutional traders’ behaviour in an emerging stock market: empirical evidence on Polish pension fund investors”. *Journal of Business, Finance and Accounting*, 32, 1537-1560.

Walter, A., & Weber, M. (2006). Herding in the German mutual fund industry. European Financial Management, 12,375-406.

Watanabe, T. (2002). Margin requirements, positive feedback trading, and stock return autocorrelations: the case of Japan. *Applied Financial Economics*, 12, 395-403.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54, 581-622.Wylie, S. (2005). Fund manager herding: a test of the accuracy of empirical results using U.K. data. *Journal of Business*, 78, 381-403.

Yang, J. J. W., 2002, “The Information Spillover Between Stock Returns and Institutional Investors’ Trading Behaviour in Taiwan”, *International Review of Financial Analysis*, 11, 533-547.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1: Descriptive statistics** | | | | | | | |
|  | Mean | Variance | Maximum | Minimum | Skewness | Exc. Kurtosis | Jarque-Bera |
| Albanian Lek | 0.0060 | 0.3147 | 4.5064 | -4.0484 | 0.0499  (0.1699) | 3.6101  (0.0000) | 2468.8878  (0.0000) |
| Algerian Dinar | -0.0102 | 0.2636 | 3.1942 | -4.4612 | -0.2417  (0.0000) | 8.6002  (0.0000) | 14044.9382  (0.0000) |
| Argentine Peso | -0.0708 | 1.3314 | 17.1207 | -34.1761 | -12.6588  (0.000) | 348.7773  (0.000) | 23147828.0575  (0.000) |
| Australian Dollar | 0.0067 | 0.6203 | 7.1562 | -7.7366 | -0.3046  (0.000) | 7.7803  (0.000) | 11528.6947  (0.000) |
| Bangladeshi Taka | -0.0096 | 0.0723 | 5.2755 | -5.7098 | -4.0898  (0.000) | 158.0901  (0.000) | 4743530.9799  (0.000) |
| Botswanan Pula | -0.0136 | 0.5631 | 4.2742 | -12.5516 | -1.7419  (0.000) | 25.4471  (0.000) | 124874.1972  (0.000) |
| Brazilian Real | -0.0142 | 1.1846 | 10.5035 | -8.2982 | -0.1402  (0.0001) | 7.5212  (0.000) | 10722.8862  (0.000) |
| Brunei Dollar | 0.0057 | 0.1136 | 2.3375 | -2.1395 | 0.0417  (0.2518) | 4.7350  (0.000) | 4245.2385  (0.000) |
| Bulgarian Lev | 0.0047 | 0.3659 | 4.6126 | -3.8484 | 0.0982  (0.0069) | 2.5995  (0.000) | 1286.4533  (0.000) |
| Canadian Dollar | 0.0034 | 0.3457 | 5.0462 | -4.3375 | 0.0924  (0.0111) | 4.9446  (0.000) | 4634.4180  (0.000) |
| Benin CFA (Franc) | 0.0047 | 0.3695 | 4.6170 | -3.8441 | 0.0876  (0.016) | 2.6075  (0.000) | 1292.8220  (0.000) |
| Chilean Peso | -0.0020 | 0.4308 | 4.3499 | -4.7628 | -0.1766  (0.000) | 3.4306  (0.000) | 2251.3391  (0.000) |
| Chinese Yuan | 0.0056 | 0.0166 | 1.9797 | -1.8362 | 0.2826  (0.000) | 30.0036  (0.000) | 170463.3128  (0.000) |
| Colombian Peso | -0.0056 | 0.5528 | 10.8406 | -8.3881 | 0.2406  (0.000) | 19.1557  (0.000) | 69502.4800  (0.000) |
| Croatian Kuna | 0.0053 | 0.3938 | 4.6191 | -3.8286 | 0.0797  (0.0283) | 2.4010  (0.000) | 1096.0094  (0.000) |
| Czech Koruna | 0.0115 | 0.5552 | 5.2192 | -5.5398 | 0.0216  (0.5532) | 3.9438  (0.000) | 2944.4722  (0.000) |
| Danish Krone | 0.0047 | 0.3673 | 4.6234 | -3.8556 | 0.0939  (0.0098) | 2.6431  (0.000) | 1329.0307  (0.000) |
| Egyptian Pound | -0.0336 | 0.9195 | 6.4590 | -53.9593 | -40.9284  (0.000) | 2228.4628  (0.000) | 941299525.2897  (0.000) |
| Euro | 0.004679 | 0.36951 | 4.6174 | -3.84447 | 0.08773  (0.0158) | 2.6089  (0.000) | 1294.215  (0.000) |
| Fijian Dollar | 0.0009 | 0.5220 | 3.9760 | -22.2582 | -6.5218  (0.000) | 201.1378  (0.000) | 7690264.0479  (0.000) |
| Gambian Dalasi | -0.0250 | 0.9394 | 14.7229 | -15.4809 | 0.0061  (0.867) | 56.4098  (0.000) | 602338.6532  (0.000) |
| Ghanaian Cedi | -0.0411 | 0.4177 | 6.1984 | -5.2530 | 0.0659  (0.0699) | 13.0294  (0.000) | 32138.5764  (0.000) |
| Hungarian Forint | 0.0006 | 0.8445 | 6.4335 | -7.8809 | -0.3867  (0.000) | 4.7968  (0.000) | 4468.7518  (0.000) |
| Indian Rupee | 0.0081 | 0.1699 | 4.0200 | -3.0065 | 0.2544  (0.000) | 8.3122  (0.000) | 13127.7309  (0.000) |
| Indonesian Rupiah | -0.0081 | 0.3531 | 8.9794 | -8.1422 | -0.0306  (0.4007) | 39.3886  (0.000) | 293680.0572  (0.000) |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1: Descriptive statistics (continued)** | | | | | | | |
|  | Mean | Variance | Maximum | Minimum | Skewness | Exc. Kurtosis | Jarque-Bera |
| Israeli Shekel | 0.0027 | 0.2289 | 2.8734 | -4.5749 | -0.2804  (0.000) | 4.8942  (0.000) | 4593.7212  (0.000) |
| Japanese Yen | 0.0011 | 0.4051 | 3.8126 | -5.1678 | 0.1407  (0.0001) | 4.0956  (0.000) | 3190.2090  (0.000) |
| Jordanian Dinar | 0.0000 | 0.0057 | 0.7090 | -0.8488 | -0.9297  (0.000) | 23.5801  (0.000) | 105904.5658  (0.000) |
| Kenyan Shilling | -0.0058 | 0.1990 | 4.6111 | -5.5633 | -0.3252  (0.000) | 25.0157  (0.000) | 118535.9386  (0.000) |
| Kazakhstan Tenge | -0.0180 | 0.4234 | 6.1078 | -24.6411 | -22.2290  (0.000) | 740.7986  (0.000) | 104254109.3627  (0.000) |
| Kuwaiti Dinar | 0.0002 | 0.0260 | 3.6104 | -3.5417 | -0.0930  (0.0105) | 133.2015  (0.000) | 3358538.8779  (0.000) |
| Latvian Lat | 0.0005 | 0.3009 | 4.5766 | -3.6590 | 0.1378  (0.0002) | 4.1568  (0.000) | 3285.1835  (0.000) |
| Lithuanian Lita | 0.0065 | 0.3406 | 4.6176 | -3.8376 | 0.0914  (0.0119) | 3.2189  (0.000) | 1967.6427  (0.000) |
| Malaysian Ringgit | -0.0011 | 0.1415 | 3.5960 | -3.1595 | 0.3486  (0.000) | 8.4861  (0.000) | 13723.6896  (0.000) |
| Maltese Lira | 0.0036 | 0.3323 | 4.6091 | -3.8539 | 0.0920  (0.0114) | 3.2698  (0.000) | 2030.2629  (0.000) |
| Mauritius Rupee | -0.0050 | 0.1563 | 2.7200 | -4.5501 | -0.5610  (0.000) | 10.1546  (0.000) | 19757.3445  (0.000) |
| Mexican Peso | -0.0158 | 0.4636 | 4.7656 | -7.5518 | -0.7706  (0.000) | 11.5763  (0.000) | 25816.8127  (0.000) |
| Moroccan Dirham | 0.0023 | 0.2302 | 3.7616 | -4.8537 | -0.1421  (0.0001) | 5.1655  (0.000) | 5066.0775  (0.000) |
| N. Zealand Dollar | 0.0100 | 0.6942 | 5.8778 | -6.6456 | -0.3994  (0.000) | 5.2704  (0.000) | 5378.8492  (0.000) |
| Nigerian Naira | -0.0262 | 0.5424 | 7.7101 | -26.9047 | -13.8530  (0.000) | 460.4542  (0.000) | 40278556.2859  (0.000) |
| Norwegian Krone | 0.0016 | 0.5770 | 6.4581 | -5.0151 | -0.0342  (0.3469) | 4.2965  (0.000) | 3495.2059  (0.000) |
| Peruvian Sol | 0.0017 | 0.0977 | 2.6615 | -3.0886 | -0.0534  (0.1419) | 10.0716  (0.000) | 19203.4523  (0.000) |
| Philippine Peso | -0.0011 | 0.1909 | 11.0961 | -4.4165 | 3.3421  (0.000) | 98.5895  (0.000) | 1848350.0647  (0.000) |
| Polish Zloty | 0.0023 | 0.7219 | 6.6973 | -5.6962 | -0.1852  (0.000) | 4.7156  (0.000) | 4235.1637  (0.000) |
| Qatari Rial | 0.0000 | 0.0011 | 1.0146 | -0.8107 | 4.7522  (0.000) | 394.4296  (0.000) | 29466094.0865  (0.000) |
| Romanian Leu | -0.0096 | 0.5110 | 5.2605 | -7.3596 | -0.3491  (0.000) | 8.2221  (0.000) | 12889.0216  (0.000) |
| Russian Rouble | -0.0171 | 0.6237 | 15.5230 | -14.2683 | -0.2490  (0.000) | 68.1609  (0.000) | 879479.6862  (0.000) |
| Singapore Dollar | 0.0057 | 0.1133 | 2.3235 | -2.6678 | -0.0183  (0.6145) | 4.3447  (0.000) | 3573.3730  (0.000) |
| Slovak Koruna | 0.0130 | 0.4114 | 4.6173 | -3.7893 | 0.0869  (0.0168) | 2.2309  (0.000) | 947.8365  (0.000) |
| Slovenian Tolar | 0.0021 | 0.3722 | 4.6172 | -3.8441 | 0.0647  (0.0752) | 2.6879  (0.000) | 1370.7595  (0.000) |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1: Descriptive statistics (continued)** | | | | | | | |
|  | Mean | Variance | Maximum | Minimum | Skewness | Exc. Kurtosis | Jarque-Bera |
| Sri Lankan Rupee | -0.0143 | 0.0597 | 4.2048 | -4.3175 | -1.9907  (0.000) | 82.8245  (0.000) | 1301522.3375  (0.000) |
| S. African Rand | -0.0112 | 1.1545 | 8.5231 | -9.8076 | -0.2868  (0.000) | 4.9226  (0.000) | 4649.1866  (0.000) |
| S. Korean Won | 0.0035 | 0.4443 | 13.2646 | -10.3506 | 0.6411  (0.000) | 54.9538  (0.000) | 571957.0993  (0.000) |
| Swedish Krona | 0.0015 | 0.5571 | 5.5474 | -3.5411 | 0.1324  (0.0003) | 3.4345  (0.000) | 2246.1046  (0.000) |
| Swiss Franc | 0.0108 | 0.5068 | 17.1413 | -9.0897 | 2.7068  (0.000) | 80.8859  (0.000) | 1243994.3999  (0.000) |
| Taiwan New Dollar | 0.0021 | 0.0639 | 1.7325 | -1.6285 | 0.0795  (0.0287) | 5.0612  (0.000) | 4853.6477  (0.000) |
| Tanzanian Shilling | -0.0229 | 0.2836 | 10.1389 | -9.4187 | 1.2053  (0.000) | 93.5835  (0.000) | 1658891.1435  (0.000) |
| Thai Baht | 0.0066 | 0.1226 | 6.9252 | -9.1332 | -2.2733  (0.000) | 138.9472  (0.000) | 3658440.6777  (0.000) |
| Tunisian Dinar | -0.0141 | 0.3767 | 9.5454 | -4.4037 | 0.6217  (0.000) | 16.8173  (0.000) | 53828.6878  (0.000) |
| Turkish Lira | -0.0418 | 1.3093 | 16.2519 | -37.4621 | -8.2147  (0.000) | 278.0793  (0.000) | 14688656.5620  (0.000) |
| UK Pound | -0.0026 | 0.3556 | 4.4737 | -8.3113 | -0.6471  (0.000) | 11.8598  (0.000) | 26942.0140  (0.000) |
| Ukrainian Hryvnia | -0.0346 | 1.4329 | 21.3927 | -39.8778 | -7.6376  (0.000) | 336.0702  (0.000) | 21423365.7563  (0.000) |
| Uruguayan Peso | -0.0200 | 0.4789 | 8.2587 | -17.6824 | -3.8537  (0.000) | 116.7641  (0.000) | 2592021.2129  (0.000) |
| Ugandan New Shilling | -0.0166 | 0.2958 | 6.1076 | -6.2576 | -0.2721  (0.000) | 22.8747  (0.000) | 99103.6614  (0.000) |
| Vanuatu Vatu | 0.0055 | 0.3084 | 3.3451 | -5.4588 | -0.6327  (0.000) | 10.7267  (0.000) | 22083.5410  (0.000) |
| Zambian Kwacha | -0.0182 | 1.1745 | 15.4524 | -14.8324 | 0.6722  (0.000) | 29.2620  (0.000) | 162426.2325  (0.000) |

The table presents the following descriptive statistics for the full sample window (29/12/2000-31/5/2018) with respect to each currency’s log-differenced returns: Mean, Variance, Maximum, Minimum, Skewness, Excess Kurtosis and the Jarque-Bera test statistic. Parentheses in the last three columns correspond to p-values.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |
| Albanian Lek | 0.0278  (0.0671) | -0.0704  (0.2222) | -0.0291  (0.2706) | 0.0140  (0.8341) | 0.0011  (0.0794) | 0.9707  (0.0000) | 0.0190  (0.0011) | 0.0125  (0.0358) |
| Algerian Dinar | -0.0105  (0.1165) | -0.0092  (0.8087) | -0.2024  (0.0000) | -0.0464  (0.2058) | 0.0029  (0.0541) | 0.9018  (0.0000) | 0.0836  (0.0000) | 0.0119  (0.6582) |
| Argentine Peso | -0.0363  (0.5752) | -0.0390  (0.0000) | -0.0665  (0.0863) | -0.0012  (0.0000) | 0.4696  (0.2089) | 0.0260  (0.2825) | 0.6793  (0.0000) | 6.4696  (0.0000) |
| Australian Dollar | 0.0147  (0.3067) | -0.0144  (0.6118) | -0.0142  (0.4140) | -0.0051  (0.6447) | 0.0053  (0.0001) | 0.9337  (0.0000) | 0.0381  (0.0000) | 0.0360  (0.0007) |
| Bangladeshi Taka | -0.0076  (0.5549) | -0.0035  (0.9169) | -0.2768  (0.0069) | 0.0259  (0.0823) | 0.0039  (0.0968) | 0.7655  (0.0000) | 0.3537  (0.3030) | -0.0997  (0.7607) |
| Botswanan Pula | -0.0226  (0.0829) | 0.0293  (0.1466) | -0.0711  (0.0091) | 0.0053  (0.3831) | 0.0025  (0.1565) | 0.9518  (0.0000) | 0.0312  (0.0049) | 0.0313  (0.1543) |
| Brazilian Real | 0.0023  (0.8854) | -0.0087  (0.5917) | -0.0318  (0.1407) | -0.0083  (0.1730) | 0.0207  (0.0040) | 0.8644  (0.0000) | 0.0697  (0.0000) | 0.1039  (0.0001) |
| Brunei Dollar | 0.0130  (0.1498) | -0.0733  (0.4678) | 0.0371  (0.1347) | -0.3372  (0.0260) | 0.0012  (0.0003) | 0.9403  (0.0000) | 0.0402  (0.0000) | 0.0199  (0.0215) |
| Bulgarian Lev | 0.0213  (0.2149) | -0.0504  (0.3402) | 0.0079  (0.7487) | -0.0305  (0.5150) | 0.0010  (0.0795) | 0.9686  (0.0000) | 0.0227  (0.0000) | 0.0124  (0.0373) |
| Canadian Dollar | -0.0052  (0.6770) | 0.0262  (0.5545) | -0.0078  (0.7024) | 0.0022  (0.9419) | 0.0016  (0.0032) | 0.9533  (0.0000) | 0.0350  (0.0000) | 0.0143  (0.1154) |
| Benin CFA (Franc) | 0.0187  (0.2678) | -0.0432  (0.4032) | 0.0099  (0.6822) | -0.0342  (0.4570) | 0.0009  (0.0663) | 0.9693  (0.0000) | 0.0218  (0.0001) | 0.0131  (0.0424) |
| Chilean Peso | 0.0040  (0.7856) | -0.0138  (0.6803) | 0.0030  (0.9042) | 0.0222  (0.5414) | 0.0041  (0.1574) | 0.9367  (0.0000) | 0.0466  (0.0027) | 0.0175  (0.3030) |
| Chinese Yuan | 0.0059  (0.3803) | 0.0067  (0.9896) | -0.1100  (0.3625) | 1.2041  (0.6781) | 0.0005  (0.6942) | 0.9215  (0.0000) | 0.0463  (0.6828) | 0.0112  (0.7693) |
| Colombian Peso | 0.0028  (0.7282) | 0.0081  (0.5717) | 0.0751  (0.0003) | -0.0073  (0.0230) | 0.0068  (0.0081) | 0.8280  (0.0000) | 0.1364  (0.0000) | 0.0905  (0.0125) |
| Croatian Kuna | 0.0146  (0.3747) | -0.0276  (0.5747) | 0.0096  (0.6939) | -0.0286  (0.5209) | 0.0010  (0.0676) | 0.9719  (0.0000) | 0.0180  (0.0008) | 0.0154  (0.0183) |
| Czech Koruna | 0.0264  (0.1103) | -0.0272  (0.4154) | 0.0188  (0.1619) | -0.0122  (0.5262) | 0.0030  (0.0169) | 0.9525  (0.0000) | 0.0388  (0.0000) | 0.0073  (0.4190) |
| Danish Krone | 0.0186  (0.2407) | -0.0428  (0.4050) | 0.0093  (0.7075) | -0.0322  (0.5336) | 0.0009  (0.0424) | 0.9691  (0.0000) | 0.0221  (0.0000) | 0.0127  (0.0317) |
| Egyptian Pound | 0.0260  (0.7039) | -0.0727  (0.0940) | -0.2409  (0.0965) | -0.0007  (0.2872) | 0.8622  (0.1626) | -0.0125  (0.4417) | 0.2467  (0.2690) | 0.0230  (0.9106) |
| Euro | 0.0187  (0.2256) | -0.0432  (0.3871) | 0.0099  (0.6992) | -0.0342  (0.4883) | 0.0009  (0.0559) | 0.9693  (0.0000) | 0.0218  (0.0001) | 0.0131  (0.0419) |
| Fijian Dollar | 0.0643  (0.3424) | -0.1284  (0.4349) | -0.2794  (0.0000) | 0.0298  (0.1996) | 0.0109  (0.1051) | 0.9232  (0.0000) | 0.1216  (0.1778) | -0.1106  (0.2807) |
| Gambian Dalasi | -0.0043  (0.7818) | -0.0267  (0.2092) | -0.2059  (0.0000) | 0.0151  (0.0741) | 0.0022  (0.2398) | 0.9719  (0.0000) | 0.0395  (0.0120) | -0.0181  (0.2834) |
| Ghanaian Cedi | -0.0207  (0.0001) | -0.0767  (0.0006) | -0.3385  (0.0000) | 0.0714  (0.0000) | 0.0026  (0.0035) | 0.8754  (0.0000) | 0.1066  (0.0000) | 0.0501  (0.0293) |
| Hungarian Forint | -0.0117  (0.5926) | 0.0183  (0.5334) | -0.0048  (0.8211) | -0.0088  (0.5802) | 0.0092  (0.0621) | 0.9454  (0.0000) | 0.0290  (0.0163) | 0.0258  (0.0609) |
| Indian Rupee | -0.0034  (0.1763) | 0.0339  (0.1753) | 0.0290  (0.1362) | -0.0516  (0.0512) | 0.0004  (0.0213) | 0.8514  (0.0000) | 0.1922  (0.0000) | -0.0393  (0.0618) |
| Indonesian Rupiah | -0.0072  (0.2219) | -0.0058  (0.8251) | 0.0628  (0.0263) | -0.0193  (0.1971) | 0.0004  (0.2373) | 0.9378  (0.0000) | 0.0559  (0.0166) | 0.0367  (0.0670) |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model (continued)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |
| Israeli Shekel | 0.0086  (0.3619) | -0.0273  (0.6152) | 0.0489  (0.0430) | -0.0326  (0.6071) | 0.0015  (0.0113) | 0.9393  (0.0000) | 0.0563  (0.0000) | -0.0027  (0.7735) |
| Japanese Yen | -0.0133  (0.4645) | 0.0335  (0.5256) | 0.0423  (0.1269) | -0.1099  (0.0149) | 0.0080  (0.0073) | 0.9274  (0.0000) | 0.0696  (0.0003) | -0.0336  (0.0630) |
| Jordanian Dinar | 0.0001  (0.8752) | 0.4839  (0.2689) | -0.3970  (0.0000) | -1.0400  (0.5718) | 0.0000  (0.0717) | 0.9313  (0.0000) | 0.1637  (0.0000) | -0.1487  (0.0000) |
| Kenyan Shilling | -0.0097  (0.0046) | 0.0343  (0.3123) | -0.0074  (0.7729) | 0.0094  (0.6800) | 0.0016  (0.1943) | 0.8681  (0.0000) | 0.1479  (0.0000) | -0.0177  (0.6559) |
| Kazakhstan Tenge | -0.0198  (0.0095) | -0.0192  (0.2077) | 0.1209  (0.0406) | -0.0012  (0.0919) | 0.0718  (0.2183) | 0.3050  (0.0276) | 0.2162  (0.0279) | 1.3241  (0.0664) |
| Kuwaiti Dinar | 0.0007  (0.7079) | 0.1895  (0.1500) | -0.1446  (0.0000) | -0.1436  (0.0418) | 0.0003  (0.2010) | 0.8314  (0.0000) | 0.2428  (0.0054) | -0.0862  (0.4004) |
| Latvian Lat | 0.0151  (0.0680) | -0.0530  (0.1073) | 0.0177  (0.3506) | -0.0415  (0.3103) | 0.0004  (0.0910) | 0.9667  (0.0000) | 0.0242  (0.0000) | 0.0167  (0.0072) |
| Lithuanian Lita | 0.0021  (0.2649) | 0.0019  (0.9273) | -0.0025  (0.9303) | -0.0054  (0.8903) | 0.0000  (0.6256) | 0.9214  (0.0000) | 0.0875  (0.0000) | 0.0037  (0.7931) |
| Malaysian Ringgit | 0.0027  (0.4189) | -0.0236  (0.6081) | -0.0260  (0.6032) | -0.0666  (0.4549) | 0.0002  (0.5220) | 0.9256  (0.0000) | 0.0818  (0.3795) | -0.0001  (0.9965) |
| Maltese Lira | 0.0213  (0.1565) | -0.0570  (0.2867) | 0.0031  (0.8913) | -0.0176  (0.7297) | 0.0009  (0.0448) | 0.9693  (0.0000) | 0.0209  (0.0001) | 0.0143  (0.0281) |
| Mauritius Rupee | -0.0141  (0.0001) | 0.0486  (0.1675) | -0.2191  (0.0000) | 0.0565  (0.0806) | 0.0001  (0.2895) | 0.8961  (0.0000) | 0.1499  (0.0000) | -0.0448  (0.0202) |
| Mexican Peso | -0.0011  (0.9025) | -0.0271  (0.2531) | 0.0278  (0.1225) | -0.0063  (0.6596) | 0.0033  (0.0267) | 0.9185  (0.0000) | 0.0430  (0.0053) | 0.0650  (0.0003) |
| Moroccan Dirham | 0.0196  (0.0785) | -0.0760  (0.1888) | -0.0220  (0.3254) | 0.0108  (0.8699) | 0.0005  (0.0515) | 0.9690  (0.0000) | 0.0256  (0.0001) | 0.0068  (0.3179) |
| N. Zealand Dollar | -0.0036  (0.8561) | 0.0216  (0.5165) | 0.0195  (0.3259) | -0.0021  (0.9096) | 0.0045  (0.0048) | 0.9593  (0.0000) | 0.0200  (0.0007) | 0.0257  (0.0004) |
| Nigerian Naira | -0.0070  (0.8132) | -0.0104  (0.8020) | -0.0533  (0.6847) | 0.0007  (0.8688) | 0.1326  (0.2353) | 0.6016  (0.0000) | 0.1428  (0.2115) | 0.2604  (0.4022) |
| Norwegian Krone | 0.0051  (0.8010) | -0.0023  (0.9548) | 0.0636  (0.0064) | -0.0683  (0.0098) | 0.0032  (0.0035) | 0.9609  (0.0000) | 0.0298  (0.0000) | 0.0070  (0.3629) |
| Peruvian Sol | 0.0052  (0.0543) | -0.0277  (0.5298) | -0.0404  (0.1833) | -0.0803  (0.1871) | 0.0005  (0.1986) | 0.8662  (0.0000) | 0.1271  (0.0349) | 0.0661  (0.1915) |
| Philippine Peso | -0.0138  (0.1925) | 0.0784  (0.2166) | -0.1096  (0.0000) | -0.0225  (0.0855) | 0.0043  (0.3116) | 0.8814  (0.0000) | 0.0920  (0.1396) | 0.0210  (0.4811) |
| Polish Zloty | 0.0268  (0.0964) | -0.0275  (0.3004) | 0.0460  (0.0240) | -0.0130  (0.4006) | 0.0067  (0.0018) | 0.9319  (0.0000) | 0.0444  (0.0000) | 0.0264  (0.0652) |
| Qatari Rial | -0.0006  (0.6356) | 1.7157  (0.1916) | -0.3660  (0.0000) | 1.3606  (0.7195) | 0.0001  (0.1668) | 0.4961  (0.0000) | 0.1504  (0.0983) | 0.1386  (0.2777) |
| Romanian Leu | -0.0569  (0.0000) | 0.0783  (0.0001) | 0.0086  (0.6589) | -0.0250  (0.1064) | 0.0001  (0.1328) | 0.9336  (0.0000) | 0.0845  (0.0000) | -0.0233  (0.0825) |
| Russian Rouble | -0.0062  (0.0499) | -0.0041  (0.7177) | 0.0590  (0.0004) | -0.0052  (0.3046) | 0.0003  (0.0112) | 0.9117  (0.0000) | 0.0765  (0.0000) | 0.0415  (0.0067) |
| Singapore Dollar | 0.0126  (0.0980) | -0.0696  (0.3537) | 0.0032  (0.8806) | -0.1669  (0.2032) | 0.0010  (0.0006) | 0.9449  (0.0000) | 0.0361  (0.0001) | 0.0213  (0.0325) |
| Slovak Koruna | 0.0064  (0.7393) | 0.0092  (0.8570) | 0.0190  (0.4523) | -0.0300  (0.5370) | 0.0011  (0.1204) | 0.9715  (0.0000) | 0.0182  (0.0038) | 0.0157  (0.0290) |
| Slovenian Tolar | 0.0160  (0.3299) | -0.0420  (0.4096) | 0.0023  (0.9244) | -0.0205  (0.6735) | 0.0010  (0.0545) | 0.9699  (0.0000) | 0.0221  (0.0005) | 0.0110  (0.1148) |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model (continued)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |
| Sri Lankan Rupee | -0.0035  (0.0857) | -0.1680  (0.0000) | 0.0468  (0.2106) | -0.0557  (0.0258) | 0.0016  (0.1412) | 0.6396  (0.0000) | 0.3533  (0.0021) | 0.5138  (0.2423) |
| S. African Rand | -0.0394  (0.0491) | 0.0272  (0.1563) | 0.0393  (0.0761) | -0.0062  (0.6062) | 0.0136  (0.0162) | 0.9254  (0.0000) | 0.0446  (0.0001) | 0.0369  (0.0060) |
| S. Korean Won | 0.0117  (0.1549) | -0.0090  (0.7375) | -0.0163  (0.2898) | -0.0057  (0.2592) | 0.0035  (0.0043) | 0.9186  (0.0000) | 0.0505  (0.0000) | 0.0374  (0.0052) |
| Swedish Krona | 0.0040  (0.8580) | -0.0024  (0.9599) | 0.0113  (0.6177) | -0.0239  (0.4591) | 0.0031  (0.0090) | 0.9630  (0.0000) | 0.0227  (0.0038) | 0.0163  (0.0297) |
| Swiss Franc | 0.0569  (0.0486) | -0.0766  (0.0013) | -0.0491  (0.0432) | -0.0012  (0.9333) | 0.0026  (0.0404) | 0.9623  (0.0000) | 0.0098  (0.4000) | 0.0590  (0.0352) |
| Taiwan New Dollar | 0.0099  (0.0310) | -0.1632  (0.0851) | 0.1329  (0.0000) | -0.9134  (0.0005) | 0.0012  (0.0180) | 0.8940  (0.0000) | 0.0863  (0.0000) | 0.0147  (0.4252) |
| Tanzanian Shilling | -0.0068  (0.0070) | -0.0214  (0.1681) | -0.0910  (0.0000) | 0.0028  (0.4618) | 0.0007  (0.0058) | 0.8209  (0.0000) | 0.2101  (0.0000) | 0.0313  (0.3481) |
| Thai Baht | 0.0162  (0.0016) | -0.0648  (0.0575) | 0.0525  (0.0092) | -0.0160  (0.0004) | 0.0049  (0.0002) | 0.7833  (0.0000) | 0.1995  (0.0000) | -0.0288  (0.4625) |
| Tunisian Dinar | -0.0094  (0.4086) | -0.0293  (0.4784) | -0.1071  (0.0000) | -0.1501  (0.0001) | 0.0013  (0.0913) | 0.9624  (0.0000) | 0.0163  (0.0386) | 0.0363  (0.0003) |
| Turkish Lira | 0.0556  (0.0723) | -0.1875  (0.0001) | -0.0092  (0.6644) | 0.0157  (0.0000) | -0.0013  (0.3266) | 0.9994  (0.0000) | -0.0247  (0.0000) | 0.0544  (0.0000) |
| UK Pound | 0.0201  (0.2114) | -0.0549  (0.2441) | -0.0132  (0.4778) | 0.0510  (0.0514) | 0.0025  (0.0218) | 0.9414  (0.0000) | 0.0494  (0.0207) | 0.0056  (0.7114) |
| Ukrainian Hryvnia | -0.0051  (0.0708) | -0.0096  (0.2541) | -0.1941  (0.0000) | 0.0001  (0.6641) | 0.0002  (0.0509) | 0.8337  (0.0000) | 0.1759  (0.0000) | 0.2012  (0.0846) |
| Uruguayan Peso | -0.0006  (0.9284) | -0.0270  (0.1302) | -0.0186  (0.7022) | -0.0059  (0.2661) | 0.0036  (0.4165) | 0.9229  (0.0000) | 0.0633  (0.0659) | 0.0401  (0.2253) |
| Ugandan New Shilling | -0.0137  (0.0052) | -0.0061  (0.7126) | -0.0368  (0.1669) | 0.0095  (0.3265) | 0.0023  (0.0241) | 0.8165  (0.0000) | 0.2116  (0.0000) | 0.0187  (0.5776) |
| Vanuatu Vatu | -0.0044  (0.6619) | 0.0333  (0.4763) | -0.0358  (0.0664) | -0.1417  (0.0004) | 0.0017  (0.0231) | 0.9673  (0.0000) | 0.0133  (0.0915) | 0.0222  (0.0255) |
| Zambian Kwacha | -0.0262  (0.0325) | 0.0116  (0.4099) | 0.0131  (0.5873) | 0.0032  (0.1308) | 0.0120  (0.0048) | 0.8431  (0.0000) | 0.2013  (0.0000) | -0.0404  (0.2369) |

The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (29/12/2000- 31/5/2018):

Parentheses include p-values.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for directional asymmetry** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |  | |
| Albanian Lek | 0.0281  (0.0911) | -0.0689  (0.2691) | -0.0291  (0.0008) | 0.0139  (0.4682) | -0.0018  (0.9368) | 0.0011  (0.0284) | 0.9707  (0.0000) | 0.0190  (0.0004) | 0.0125  (0.0690) | |
| Algerian Dinar | -0.0068  (0.3934) | 0.0221  (0.6237) | -0.2023  (0.0000) | -0.0472  (0.1508) | -0.0390  (0.1554) | 0.0029  (0.0653) | 0.9019  (0.0000) | 0.0829  (0.0001) | 0.0131  (0.6218) | |
| Argentine Peso | 0.1708  (0.0000) | 0.0025  (0.0485) | 0.1904  (0.0916) | 0.0000  (0.9390) | -1.2282  (0.0000) | 0.0149  (0.0136) | 0.3429  (0.0035) | 0.6281  (0.0140) | 11.4586  (0.3027) | |
| Australian Dollar | 0.0279  (0.0554) | 0.0171  (0.4578) | -0.0142  (0.3580) | -0.0051  (0.5283) | -0.0591  (0.0062) | 0.0052  (0.0002) | 0.9344  (0.0000) | 0.0379  (0.0000) | 0.0356  (0.0009) | |
| Bangladeshi Taka | -0.0071  (0.5712) | 0.0083  (0.9225) | -0.2898  (0.0698) | 0.0270  (0.4546) | -0.0326  (0.8406) | 0.0039  (0.1134) | 0.7651  (0.0000) | 0.3505  (0.3173) | -0.0940  (0.7633) | |
| Botswanan Pula | -0.0267  (0.0613) | 0.0244  (0.2851) | -0.0709  (0.0000) | 0.0063  (0.2471) | 0.0146  (0.5734) | 0.0026  (0.0271) | 0.9518  (0.0000) | 0.0311  (0.0001) | 0.0315  (0.1346) | |
| Brazilian Real | -0.0031  (0.8624) | -0.0171  (0.3773) | -0.0332  (0.1108) | -0.0080  (0.2298) | 0.0215  (0.4219) | 0.0206  (0.0026) | 0.8647  (0.0000) | 0.0697  (0.0000) | 0.1035  (0.0001) | |
| Brunei Dollar | 0.0147  (0.0535) | -0.0407  (0.6122) | 0.0377  (0.1084) | -0.3366  (0.0233) | -0.0225  (0.3861) | 0.0012  (0.0000) | 0.9403  (0.0000) | 0.0401  (0.0000) | 0.0201  (0.0634) | |
| Bulgarian Lev | 0.0305  (0.0437) | -0.0024  (0.9625) | 0.0094  (0.7054) | -0.0307  (0.5584) | -0.0601  (0.0080) | 0.0010  (0.0726) | 0.9688  (0.0000) | 0.0227  (0.0001) | 0.0119  (0.0654) | |
| Canadian Dollar | -0.0003  (0.9805) | 0.0471  (0.2975) | -0.0075  (0.6667) | 0.0024  (0.9123) | -0.0288  (0.1807) | 0.0016  (0.0098) | 0.9529  (0.0000) | 0.0354  (0.0000) | 0.0139  (0.1192) | |
| Benin CFA (Franc) | 0.0281  (0.0621) | 0.0040  (0.9369) | 0.0113  (0.6375) | -0.0343  (0.4860) | -0.0600  (0.0075) | 0.0009  (0.0813) | 0.9695  (0.0000) | 0.0219  (0.0001) | 0.0126  (0.0403) | |
| Chilean Peso | 0.0068  (0.6522) | 0.0041  (0.9172) | 0.0038  (0.8728) | 0.0205  (0.5635) | -0.0232  (0.3868) | 0.0041  (0.1620) | 0.9369  (0.0000) | 0.0465  (0.0008) | 0.0172  (0.3265) | |
| Chinese Yuan | 0.0058  (0.2510) | 0.1584  (0.7822) | -0.1094  (0.4410) | 1.2895  (0.7337) | -0.0369  (0.5564) | 0.0005  (0.7173) | 0.9254  (0.0000) | 0.0434  (0.7071) | 0.0123  (0.6423) | |
| Colombian Peso | 0.0033  (0.716) | 0.0092  (0.5495) | 0.0753  (0.0001) | -0.0074  (0.0023) | -0.0027  (0.9122) | 0.0068  (0.0015) | 0.8281  (0.0000) | 0.1363  (0.0000) | 0.0906  (0.0206) | |
| Croatian Kuna | 0.0194  (0.2455) | -0.0057  (0.9096) | 0.0105  (0.6768) | -0.0290  (0.5232) | -0.0291  (0.1524) | 0.0010  (0.0677) | 0.9719  (0.0000) | 0.0181  (0.0007) | 0.0152  (0.0238) | |
| Czech Koruna | 0.0310  (0.0489) | -0.0115  (0.7276) | 0.0200  (0.3503) | -0.0131  (0.5645) | -0.0249  (0.3089) | 0.0030  (0.0060) | 0.9528  (0.0000) | 0.0388  (0.0000) | 0.0069  (0.4462) | |
| Danish Krone | 0.0285  (0.0070) | 0.0075  (0.7353) | 0.0107  (0.6571) | -0.0321  (0.4848) | -0.0638  (0.0037) | 0.0009  (0.0691) | 0.9693  (0.0000) | 0.0222  (0.0001) | 0.0122  (0.0630) | |
| Egyptian Pound | 0.0330  (0.7360) | -0.0844  (0.2979) | -0.2398  (0.0000) | -0.0009  (0.4991) | 0.0260  (0.7939) | 0.8624  (0.1791) | -0.0127  (0.3179) | 0.2469  (0.0367) | 0.0229  (0.8984) | |
| Euro | 0.0281  (0.0694) | 0.0041  (0.9317) | 0.0113  (0.6594) | -0.0343  (0.5087) | -0.0602  (0.0068) | 0.0009  (0.0590) | 0.9695  (0.0000) | 0.0219  (0.0001) | 0.0126  (0.0650) | |
| Fijian Dollar | 0.0451  (0.4733) | -0.1507  (0.3558) | -0.2733  (0.0000) | 0.0323  (0.1839) | 0.0767  (0.0742) | 0.0117  (0.1111) | 0.9176  (0.0000) | 0.1312  (0.1767) | -0.1185  (0.2738) | |
| Gambian Dalasi | -0.0074  (0.6774) | -0.0332  (0.2072) | -0.2005  (0.0000) | 0.0144  (0.1345) | 0.0288  (0.3135) | 0.0022  (0.1819) | 0.9719  (0.0000) | 0.0395  (0.0206) | -0.0179  (0.3083) | |
| Ghanaian Cedi | -0.0165  (0.0231) | -0.0596  (0.0098) | -0.3398  (0.0000) | 0.0710  (0.0000) | -0.0342  (0.2466) | 0.0026  (0.0013) | 0.8755  (0.0000) | 0.1067  (0.0000) | 0.0503  (0.0285) | |
| Hungarian Forint | -0.0094  (0.7024) | 0.0227  (0.4896) | -0.0044  (0.8480) | -0.0092  (0.5756) | -0.0093  (0.6861) | 0.0092  (0.0959) | 0.9453  (0.0000) | 0.0289  (0.0147) | 0.0261  (0.0580) | |
| Indian Rupee | -0.0057  (0.0532) | -0.0085  (0.8224) | 0.0289  (0.1282) | -0.0531  (0.0625) | 0.0431  (0.1335) | 0.0004  (0.0225) | 0.8515  (0.0000) | 0.1927  (0.0000) | -0.0405  (0.0430) | |
| Indonesian Rupiah | -0.0112  (0.0711) | -0.0258  (0.2750) | 0.0621  (0.0737) | -0.0189  (0.2169) | 0.0395  (0.2523) | 0.0004  (0.2768) | 0.9376  (0.0000) | 0.0566  (0.0120) | 0.0355  (0.0784) | |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for directional asymmetry (cont.)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |  | |
| Israeli Shekel | 0.0107  (0.2794) | -0.0077  (0.8976) | 0.0488  (0.0209) | -0.0335  (0.5585) | -0.0196  (0.4525) | 0.0015  (0.0320) | 0.9396  (0.0000) | 0.0559  (0.0000) | -0.0022  (0.8478) | |
| Japanese Yen | -0.0120  (0.5526) | 0.0442  (0.4282) | 0.0413  (0.1484) | -0.1085  (0.0160) | -0.0122  (0.6583) | 0.0079  (0.0153) | 0.9279  (0.0000) | 0.0690  (0.0005) | -0.0333  (0.0744) | |
| Jordanian Dinar | 0.0002  (0.6912) | 0.7076  (0.1446) | -0.4054  (0.0000) | -0.9848  (0.5665) | -0.0450  (0.2652) | 0.0000  (0.0775) | 0.9312  (0.0000) | 0.1582  (0.0000) | -0.1421  (0.0000) | |
| Kenyan Shilling | -0.0097  (0.0213) | 0.0345  (0.3778) | -0.0074  (0.7658) | 0.0094  (0.6572) | -0.0004  (0.9910) | 0.0016  (0.0995) | 0.8681  (0.0000) | 0.1479  (0.0001) | -0.0177  (0.4580) | |
| Kazakhstan Tenge | -0.0180  (0.3032) | -0.0174  (0.1731) | 0.1282  (0.0007) | -0.0012  (0.0926) | -0.0238  (0.8535) | 0.0716  (0.2167) | 0.3066  (0.0155) | 0.2153  (0.0798) | 1.3386  (0.1602) | |
| Kuwaiti Dinar | 0.0010  (0.4985) | 0.2210  (0.0543) | -0.1466  (0.0000) | -0.1377  (0.0228) | -0.0195  (0.5769) | 0.0003  (0.1918) | 0.8312  (0.0000) | 0.2422  (0.0163) | -0.0844  (0.4340) | |
| Latvian Lat | 0.0249  (0.0144) | 0.0014  (0.9744) | 0.0191  (0.3385) | -0.0409  (0.3279) | -0.0680  (0.0045) | 0.0004  (0.0402) | 0.9670  (0.0000) | 0.0241  (0.0002) | 0.0162  (0.0325) | |
| Lithuanian Lita | 0.0023  (0.2620) | 0.0233  (0.4830) | -0.0017  (0.9508) | -0.0056  (0.9016) | -0.0206  (0.3960) | 0.0000  (0.5160) | 0.9217  (0.0000) | 0.0874  (0.0000) | 0.0032  (0.8238) | |
| Malaysian Ringgit | 0.0020  (0.3983) | -0.0782  (0.1354) | -0.0285  (0.6473) | -0.0665  (0.5666) | 0.0441  (0.2725) | 0.0002  (0.4935) | 0.9248  (0.0000) | 0.0823  (0.2957) | 0.0007  (0.9744) | |
| Maltese Lira | 0.0318  (0.0261) | -0.0051  (0.9237) | 0.0048  (0.8283) | -0.0182  (0.7233) | -0.0661  (0.0018) | 0.0009  (0.0397) | 0.9695  (0.0000) | 0.0210  (0.0000) | 0.0137  (0.0311) | |
| Mauritius Rupee | -0.0133  (0.0002) | 0.0736  (0.1133) | -0.2205  (0.0000) | 0.0558  (0.0969) | -0.0253  (0.401) | 0.0001  (0.177) | 0.8971  (0.0000) | 0.1484  (0.0000) | -0.0447  (0.0265) | |
| Mexican Peso | -0.0008  (0.943) | -0.0263  (0.3321) | 0.0278  (0.1425) | -0.0064  (0.6155) | -0.0017  (0.9382) | 0.0033  (0.0101) | 0.9185  (0.0000) | 0.0430  (0.0018) | 0.0650  (0.0003) | |
| Moroccan Dirham | 0.0281  (0.0088) | -0.0236  (0.6998) | -0.0190  (0.4339) | 0.0013  (0.9845) | -0.0600  (0.0131) | 0.0005  (0.0579) | 0.9692  (0.0000) | 0.0258  (0.0003) | 0.0059  (0.3501) | |
| N. Zealand Dollar | 0.0117  (0.5095) | 0.0500  (0.1429) | 0.0192  (0.3124) | -0.0033  (0.8412) | -0.0583  (0.0014) | 0.0046  (0.0011) | 0.9590  (0.0000) | 0.0206  (0.0001) | 0.0249  (0.0004) | |
| Nigerian Naira | 0.0035  (0.8687) | 0.0051  (0.6895) | -0.0318  (0.8062) | 0.0007  (0.6266) | -0.1148  (0.0749) | 0.1336  (0.2389) | 0.5945  (0.0000) | 0.1400  (0.1917) | 0.3184  (0.1019) | |
| Norwegian Krone | 0.0089  (0.6613) | 0.0089  (0.8318) | 0.0631  (0.0017) | -0.0685  (0.0067) | -0.0184  (0.3473) | 0.0032  (0.004) | 0.9610  (0.0000) | 0.0296  (0.0000) | 0.0073  (0.3735) | |
| Peruvian Sol | 0.0030  (0.4504) | -0.0890  (0.0751) | -0.0451  (0.1538) | -0.0737  (0.2503) | 0.0545  (0.1578) | 0.0005  (0.1875) | 0.8705  (0.0000) | 0.1236  (0.0343) | 0.0611  (0.1704) | |
| Philippine Peso | -0.0095  (0.4218) | 0.0981  (0.1439) | -0.1105  (0.0000) | -0.0216  (0.0774) | -0.0327  (0.1657) | 0.0043  (0.1344) | 0.8812  (0.0000) | 0.0908  (0.0567) | 0.0239  (0.1774) | |
| Polish Zloty | 0.0340  (0.0563) | -0.0091  (0.7697) | 0.0467  (0.0362) | -0.0140  (0.3867) | -0.0341  (0.1440) | 0.0066  (0.0110) | 0.9324  (0.0000) | 0.0440  (0.0000) | 0.0263  (0.0690) | |
| Qatari Rial | -0.0001  (0.9530) | 1.9745  (0.1517) | -0.3622  (0.0000) | 1.3346  (0.7323) | -0.1032  (0.0519) | 0.0001  (0.1995) | 0.5039  (0.0000) | 0.1434  (0.0548) | 0.1510  (0.1766) | |
| Romanian Leu | -0.0568  (0.0000) | 0.0787  (0.0008) | 0.0086  (0.6296) | -0.0250  (0.1043) | -0.0007  (0.9733) | 0.0001  (0.2057) | 0.9336  (0.0000) | 0.0845  (0.0000) | -0.0233  (0.1149) | |
| Russian Rouble | -0.0079  (0.0130) | -0.0130  (0.4056) | 0.0584  (0.0008) | -0.0050  (0.4113) | 0.0215  (0.2716) | 0.0003  (0.0099) | 0.9118  (0.0000) | 0.0761  (0.0000) | 0.0416  (0.0088) | |
| Singapore Dollar | 0.0151  (0.0474) | -0.0213  (0.7971) | 0.0050  (0.8393) | -0.1708  (0.2141) | -0.0332  (0.1590) | 0.0010  (0.0000) | 0.9449  (0.0000) | 0.0359  (0.0000) | 0.0216  (0.0252) | |
| Slovak Koruna | 0.0164  (0.3670) | 0.0531  (0.2661) | 0.0210  (0.4090) | -0.0299  (0.5160) | -0.0597  (0.0047) | 0.0011  (0.1786) | 0.9716  (0.0000) | 0.0181  (0.0009) | 0.0157  (0.0097) | |
| Slovenian Tolar | 0.0246  (0.1327) | 0.0042  (0.9362) | 0.0031  (0.9055) | -0.0203  (0.6851) | -0.0580  (0.0128) | 0.0010  (0.0657) | 0.9702  (0.0000) | 0.0219  (0.0001) | 0.0106  (0.1075) | |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for directional asymmetry (cont.)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  |  | |
| Sri Lankan Rupee | -0.0013  (0.8004) | -0.1577  (0.0000) | 0.0592  (0.0849) | -0.0647  (0.0024) | -0.0802  (0.3328) | 0.0016  (0.0660) | 0.6407  (0.0000) | 0.3482  (0.0003) | 0.5285  (0.1773) | |
| S. African Rand | -0.0400  (0.0638) | 0.0263  (0.1732) | 0.0393  (0.0586) | -0.0062  (0.5742) | 0.0022  (0.9265) | 0.0136  (0.0069) | 0.9254  (0.0000) | 0.0446  (0.0000) | 0.0369  (0.0051) | |
| S. Korean Won | 0.0065  (0.5357) | -0.0247  (0.5289) | -0.0163  (0.3802) | -0.0060  (0.2483) | 0.0292  (0.2087) | 0.0035  (0.0015) | 0.9187  (0.0000) | 0.0505  (0.0000) | 0.0372  (0.0077) | |
| Swedish Krona | 0.0138  (0.5462) | 0.0286  (0.5612) | 0.0120  (0.5905) | -0.0242  (0.4324) | -0.0489  (0.0487) | 0.0030  (0.0059) | 0.9636  (0.0000) | 0.0221  (0.0014) | 0.0164  (0.0498) | |
| Swiss Franc | 0.0500  (0.0385) | -0.0885  (0.0003) | -0.0505  (0.0231) | -0.0028  (0.8774) | 0.0279  (0.2760) | 0.0026  (0.0569) | 0.9627  (0.0000) | 0.0094  (0.3621) | 0.0589  (0.0576) | |
| Taiwan New Dollar | 0.0101  (0.0362) | -0.1386  (0.1908) | 0.1342  (0.0000) | -0.9212  (0.0003) | -0.0114  (0.7147) | 0.0012  (0.0220) | 0.8943  (0.0000) | 0.0859  (0.0000) | 0.0151  (0.4253) | |
| Tanzanian Shilling | -0.0017  (0.6159) | 0.0096  (0.5172) | -0.0979  (0.0000) | 0.0033  (0.3713) | -0.0883  (0.0002) | 0.0007  (0.0263) | 0.8208  (0.0000) | 0.2061  (0.0000) | 0.0419  (0.1629) | |
| Thai Baht | 0.0195  (0.0009) | -0.0489  (0.2037) | 0.0523  (0.0044) | -0.0163  (0.0057) | -0.0303  (0.2363) | 0.0049  (0.0010) | 0.7834  (0.0000) | 0.1989  (0.0000) | -0.0276  (0.4891) | |
| Tunisian Dinar | 0.0014  (0.9177) | 0.0158  (0.7001) | -0.1070  (0.0000) | -0.1478  (0.0001) | -0.0638  (0.0152) | 0.0012  (0.0458) | 0.9627  (0.0000) | 0.0159  (0.0186) | 0.0373  (0.0003) | |
| Turkish Lira | 0.0297  (0.1086) | -0.2085  (0.0018) | -0.0027  (0.9127) | 0.0150  (0.0009) | 0.0774  (0.1626) | -0.0011  (0.2805) | 0.9999  (0.0000) | -0.0257  (0.0000) | 0.0535  (0.0000) | |
| UK Pound | 0.0277  (0.0991) | -0.0273  (0.5928) | -0.0122  (0.5156) | 0.0478  (0.1168) | -0.0417  (0.0949) | 0.0025  (0.0095) | 0.9423  (0.0000) | 0.0491  (0.0247) | 0.0048  (0.7464) | |
| Ukrainian Hryvnia | -0.0032  (0.2474) | -0.0040  (0.5816) | -0.1875  (0.0000) | 0.0001  (0.6345) | -0.0586  (0.2686) | 0.0002  (0.1040) | 0.8340  (0.0000) | 0.1698  (0.0000) | 0.2187  (0.1580) | |
| Uruguayan Peso | 0.0021  (0.7915) | -0.0193  (0.3242) | -0.0175  (0.6961) | -0.0063  (0.1386) | -0.0243  (0.4874) | 0.0036  (0.3831) | 0.9231  (0.0000) | 0.0639  (0.0557) | 0.0389  (0.236) | |
| Ugandan New Shilling | -0.0136  (0.0055) | -0.0057  (0.7625) | -0.0368  (0.1750) | 0.0095  (0.2644) | -0.0008  (0.9797) | 0.0023  (0.0540) | 0.8165  (0.0000) | 0.2115  (0.0000) | 0.0188  (0.6023) | |
| Vanuatu Vatu | 0.0002  (0.9847) | 0.0616  (0.2187) | -0.0330  (0.0923) | -0.1482  (0.0006) | -0.0397  (0.0878) | 0.0017  (0.0299) | 0.9675  (0.0000) | 0.0138  (0.1059) | 0.0210  (0.0322) | |
| Zambian Kwacha | -0.0287  (0.1301) | 0.0089  (0.4754) | 0.0138  (0.5451) | 0.0031  (0.2280) | 0.0116  (0.7091) | 0.0120  (0.0044) | 0.8432  (0.0000) | 0.2018  (0.0000) | -0.0412  (0.2625) | |

The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (29/12/2000- 31/5/2018):

Parentheses include p-values.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 4: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for currency appreciations/depreciations** | | | | | | | | |
|  |  |  | |  | |  | | |
| Albanian Lek | -0.0813  (0.0689) | | 0.0207  (0.6398) | | 0.1738  (0.0860) | | -0.1423  (0.2276) |
| Algerian Dinar | -0.1938  (0.0000) | | -0.2011  (0.0000) | | 0.0496  (0.2529) | | -0.1767  (0.0031) |
| Argentine Peso | -0.2897  (0.0000) | | 0.1392  (0.0244) | | -0.0006  (0.0927) | | -0.0078  (0.0706) |
| Australian Dollar | 0.0422  (0.1912) | | -0.0707  (0.0175) | | 0.0001  (0.9958) | | -0.0096  (0.5557) |
| Bangladeshi Taka | -0.5286  (0.0418) | | -0.3343  (0.2348) | | 0.0422  (0.1041) | | -0.0484  (0.3666) |
| Botswanan Pula | -0.0704  (0.0534) | | -0.0550  (0.1651) | | 0.0064  (0.4065) | | 0.0034  (0.9365) |
| Brazilian Real | -0.0499  (0.1641) | | -0.0168  (0.6103) | | -0.0121  (0.2573) | | -0.0031  (0.7531) |
| Brunei Dollar | 0.0431  (0.2946) | | 0.0333  (0.4749) | | -0.2027  (0.3373) | | -0.4884  (0.1004) |
| Bulgarian Lev | 0.0399  (0.3805) | | -0.0235  (0.5820) | | 0.0452  (0.6175) | | -0.1008  (0.2292) |
| Canadian Dollar | 0.0384  (0.3015) | | -0.0477  (0.0897) | | -0.0432  (0.3772) | | 0.0367  (0.2211) |
| Benin CFA (Franc) | 0.0449  (0.2958) | | -0.0240  (0.5934) | | 0.0329  (0.6806) | | -0.0973  (0.2684) |
| Chilean Peso | 0.0236  (0.5519) | | 0.0202  (0.6016) | | 0.0247  (0.5862) | | -0.0405  (0.4999) |
| Chinese Yuan | -0.1292  (0.0335) | | -0.1096  (0.1074) | | 1.2613  (0.0000) | | 0.0174  (0.9536) |
| Colombian Peso | 0.0856  (0.0065) | | 0.0699  (0.0165) | | -0.0155  (0.1017) | | -0.0046  (0.0851) |
| Croatian Kuna | -0.0065  (0.8734) | | 0.0242  (0.5988) | | 0.0816  (0.2567) | | -0.1339  (0.1324) |
| Czech Koruna | 0.0006  (0.9880) | | 0.0307  (0.4202) | | 0.0541  (0.2317) | | -0.0740  (0.1069) |
| Danish Krone | 0.0476  (0.2328) | | -0.0279  (0.4609) | | 0.0370  (0.6278) | | -0.0965  (0.2198) |
| Egyptian Pound | -0.3038  (0.0000) | | -0.5045  (0.6173) | | 0.0000  (0.9988) | | 0.4837  (0.2674) |
| Euro | 0.0451  (0.2844) | | -0.0242  (0.5897) | | 0.0330  (0.6774) | | -0.0973  (0.2777) |
| Fijian Dollar | -0.3363  (0.0000) | | -0.2004  (0.0003) | | 0.0184  (0.0072) | | 0.0073  (0.8317) |
| Gambian Dalasi | -0.2231  (0.0000) | | -0.1781  (0.0000) | | 0.0104  (0.3451) | | 0.0177  (0.1807) |
| Ghanaian Cedi | -0.2832  (0.0000) | | -0.3989  (0.0000) | | 0.0300  (0.1468) | | 0.1100  (0.0000) |
| Hungarian Forint | 0.0146  (0.6906) | | -0.0299  (0.4078) | | -0.0199  (0.4214) | | 0.0068  (0.7742) |
| Indian Rupee | -0.0135  (0.7035) | | 0.0703  (0.0395) | | -0.0631  (0.2019) | | -0.0443  (0.4008) |
| Indonesian Rupiah | 0.0323  (0.4450) | | 0.0977  (0.0248) | | -0.0387  (0.0150) | | 0.0005  (0.9872) |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 4: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for currency appreciations/depreciations (continued)** | | | | | | | | |
|  |  |  | |  | |  | | |
| Israeli Shekel | 0.0437  (0.2721) | | 0.0647  (0.1236) | | 0.0574  (0.4498) | | -0.1674  (0.1756) |
| Japanese Yen | -0.0097  (0.7942) | | 0.0898  (0.1134) | | 0.0365  (0.4483) | | -0.2389  (0.0057) |
| Jordanian Dinar | -0.3828  (0.0000) | | -0.4218  (0.0000) | | 1.0771  (0.7470) | | -3.9095  (0.1447) |
| Kenyan Shilling | -0.0044  (0.8877) | | -0.0159  (0.6889) | | -0.0287  (0.5898) | | 0.0499  (0.3569) |
| Kazakhstan Tenge | 0.2359  (0.0059) | | 0.0977  (0.1318) | | -0.0017  (0.3740) | | -0.0031  (0.7440) |
| Kuwaiti Dinar | -0.1287  (0.0005) | | -0.1765  (0.0027) | | -0.3990  (0.0112) | | 0.0589  (0.6613) |
| Latvian Lat | 0.0925  (0.0079) | | -0.0549  (0.0962) | | -0.0597  (0.3821) | | -0.0215  (0.7690) |
| Lithuanian Lita | 0.0450  (0.3081) | | -0.0216  (0.6012) | | 0.0496  (0.5385) | | -0.1048  (0.1969) |
| Malaysian Ringgit | 0.0031  (0.9520) | | 0.1158  (0.0027) | | -0.2241  (0.0222) | | -0.2107  (0.0036) |
| Maltese Lira | 0.0512  (0.1855) | | -0.0433  (0.2571) | | 0.0370  (0.6416) | | -0.0690  (0.3969) |
| Mauritius Rupee | -0.1951  (0.0001) | | -0.2552  (0.0000) | | 0.0315  (0.337) | | 0.1157  (0.0607) |
| Mexican Peso | 0.0281  (0.3637) | | 0.0314  (0.2838) | | -0.0024  (0.9168) | | -0.0179  (0.4269) |
| Moroccan Dirham | 0.0200  (0.6077) | | -0.0537  (0.2224) | | 0.0786  (0.4320) | | -0.0967  (0.4950) |
| N. Zealand Dollar | 0.0608  (0.0550) | | -0.0232  (0.4575) | | 0.0153  (0.5734) | | -0.0234  (0.4274) |
| Nigerian Naira | 0.8330  (0.0000) | | 0.2903  (0.2508) | | 0.0013  (0.0261) | | -0.0075  (0.0004) |
| Norwegian Krone | 0.0704  (0.0860) | | 0.0538  (0.0569) | | -0.0512  (0.3213) | | -0.0818  (0.0061) |
| Peruvian Sol | -0.1029  (0.0765) | | 0.0053  (0.8854) | | -0.1275  (0.2177) | | 0.0040  (0.9717) |
| Philippine Peso | 0.0833  (0.1207) | | -0.1518  (0.0036) | | -0.9421  (0.0001) | | 0.1856  (0.3454) |
| Polish Zloty | 0.0975  (0.0080) | | -0.0045  (0.8991) | | -0.0367  (0.1753) | | 0.0101  (0.7188) |
| Qatari Rial | -0.3115  (0.0000) | | -0.4848  (0.0000) | | 2.4442  (0.2407) | | -0.4365  (0.9120) |
| Romanian Leu | -0.0084  (0.8017) | | 0.0207  (0.4894) | | 0.0134  (0.7230) | | -0.0623  (0.0009) |
| Russian Rouble | 0.0387  (0.2012) | | 0.0801  (0.0002) | | -0.0109  (0.2604) | | -0.0002  (0.9271) |
| Singapore Dollar | 0.0310  (0.4118) | | -0.0256  (0.5188) | | -0.1070  (0.5504) | | -0.2102  (0.3506) |
| Slovak Koruna | 0.0377  (0.3717) | | 0.0001  (0.9987) | | 0.0682  (0.3478) | | -0.1208  (0.1407) |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  | | --- | | **Table 4: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for currency appreciations/depreciations (continued)** | | | | | | | | | |
|  |  |  | |  | |  | | |
| Slovenian Tolar | 0.0289  (0.5063) | | -0.0248  (0.5704) | | 0.0608  (0.4416) | | -0.0960  (0.2391) |
| Sri Lankan Rupee | 0.1125  (0.4393) | | -0.0515  (0.6523) | | -0.0819  (0.0003) | | 0.1254  (0.0002) |
| S. African Rand | 0.0493  (0.2070) | | 0.0292  (0.3616) | | -0.0150  (0.4508) | | 0.0033  (0.7834) |
| S. Korean Won | -0.0431  (0.1939) | | 0.0130  (0.6482) | | -0.0163  (0.1768) | | -0.0005  (0.9468) |
| Swedish Krona | 0.0287  (0.5118) | | -0.0106  (0.7990) | | 0.0350  (0.5142) | | -0.0750  (0.2009) |
| Swiss Franc | -0.0523  (0.2349) | | -0.0343  (0.4181) | | 0.0031  (0.8838) | | 0.0060  (0.2260) |
| Taiwan New Dollar | 0.1316  (0.0120) | | 0.1382  (0.0035) | | -0.7275  (0.0466) | | -1.1300  (0.0063) |
| Tanzanian Shilling | -0.0076  (0.7685) | | -0.1980  (0.0000) | | 0.0014  (0.6261) | | 0.0056  (0.2522) |
| Thai Baht | 0.0809  (0.0119) | | 0.0258  (0.3079) | | -0.0108  (0.0843) | | -0.0487  (0.0010) |
| Tunisian Dinar | -0.0209  (0.5820) | | -0.1944  (0.0000) | | -0.2032  (0.0054) | | -0.0972  (0.0070) |
| Turkish Lira | -0.0741  (0.0000) | | 0.1930  (0.0000) | | 0.0013  (0.0000) | | -0.0716  (0.0000) |
| UK Pound | 0.0153  (0.6646) | | -0.0142  (0.6737) | | 0.0857  (0.0032) | | -0.0636  (0.1386) |
| Ukrainian Hryvnia | -0.1303  (0.0117) | | -0.2499  (0.0000) | | -0.0002  (0.6173) | | 0.0018  (0.0046) |
| Uruguayan Peso | -0.0050  (0.9498) | | -0.0465  (0.2564) | | -0.0093  (0.2398) | | 0.0051  (0.4841) |
| Ugandan New Shilling | -0.0380  (0.3777) | | -0.0352  (0.3518) | | 0.0140  (0.2404) | | 0.0057  (0.5971) |
| Vanuatu Vatu | 0.0046  (0.8851) | | -0.0762  (0.0120) | | -0.1445  (0.0042) | | -0.1284  (0.0577) |
| Zambian Kwacha | 0.0101  (0.7456) | | 0.0173  (0.6769) | | 0.0002  (0.9333) | | 0.0051  (0.1206) |

The table presents the maximum likelihood estimates of the autocorrelation and feedback parameters from the following equations for the full sample period (29/12/2000- 31/5/2018):

Dt-1 =1, if the currency has appreciated, zero otherwise. Parentheses include p-values.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model controlling for long memory** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  | Optimal lag-length |
| Albanian Lek | 0.0277  (0.0972) | -0.0755  (0.2247) | 0.0633  (0.0445) | -0.1772  (0. 0416) | 0.0012  (0.0385) | 0.9704  (0.0000) | 0.0192  (0.0029) | 0.0129  (0.0632) | 2 |
| Algerian Dinar | -0.0104  (0.1533) | -0.0035  (0.9188) | -0.0343  (0.1438) | -0.0347  (0.2591) | 0.0035  (0.0445) | 0.8900  (0.0000) | 0.0955  (0.0000) | 0.0107  (0.6543) | 4 |
| Argentine Peso | -0.0773  (0.0214) | -0.0089  (0.0516) | -0.2120  0.0000 | -0.0003  (0.0737) | 0.3823  (0.2688) | 0.1309  (0.4488) | 0.4015  (0.1417) | 6.2472  (0.4860) | 5 |
| Australian Dollar | 0.0148  (0.3379) | -0.0166  (0.5994) | 0.0104  (0.5865) | -0.0257  (0.0948) | 0.0054  (0.0000) | 0.9339  (0.0000) | 0.0371  (0.0000) | 0.0373  (0.0000) | 2 |
| Bangladeshi Taka | -0.0053  (0.3969) | 0.0113  (0.8277) | 0.2781  (0.3243) | -0.0586  (0.0434) | 0.0045  (0.0723) | 0.7324  (0.0000) | 0.4696  (0.3581) | -0.2012  (0.6560) | 4 |
| Botswanan Pula | -0.0216  (0.1052) | 0.0289  (0.1383) | 0.0066  (0.7256) | -0.0038  (0.6191) | 0.0025  (0.1675) | 0.9534  (0.0000) | 0.0293  (0.0046) | 0.0321  (0.1393) | 2 |
| Brazilian Real | 0.0031  (0.8501) | -0.0114  (0.5311) | 0.0073  (0.7380) | -0.0196  (0.0008) | 0.0201  (0.0036) | 0.8682  (0.0000) | 0.0654  (0.0000) | 0.1058  (0.0000) | 2 |
| Brunei Dollar | 0.0117  (0.1526) | -0.0615  (0.4591) | 0.0517  (0.0440) | -0.2531  (0.0664) | 0.0011  (0.0008) | 0.9408  (0.0000) | 0.0400  (0.0001) | 0.0195  (0.1048) | 5 |
| Bulgarian Lev | 0.0211  (0.2218) | -0.0509  (0.3627) | 0.0683  (0.0309) | -0.1669  (0.0253) | 0.0010  (0.0729) | 0.9685  (0.0000) | 0.0225  (0.0000) | 0.0130  (0.0389) | 2 |
| Canadian Dollar | -0.0043  (0.6982) | 0.0239  (0.5100) | 0.0217  (0.3301) | -0.0746  (0.0723) | 0.0016  (0.0030) | 0.9535  (0.0000) | 0.0347  (0.0000) | 0.0143  (0.0906) | 2 |
| Benin CFA (Franc) | 0.0186  (0.2495) | -0.0436  (0.4179) | 0.0652  (0.0434) | -0.1603  (0.0379) | 0.0009  (0.1176) | 0.9692  (0.0000) | 0.0216  (0.0003) | 0.0136  (0.0377) | 2 |
| Chilean Peso | 0.0076  (0.6666) | -0.0269  (0.4973) | 0.0312  (0.2549) | -0.0795  (0.0426) | 0.0044  (0.1191) | 0.9327  (0.0000) | 0.0493  (0.0206) | 0.0187  (0.2595) | 5 |
| Chinese Yuan | 0.0065  (0.3934) | -0.0805  (0.8439) | 0.0598  (0.0027) | -0.4047  (0.4490) | 0.0007  (0.7735) | 0.8865  (0.0071) | 0.0753  (0.7574) | -0.0035  (0.9713) | 5 |
| Colombian Peso | 0.0022  (0.7407) | 0.0118  (0.4005) | 0.0338  (0.0687) | -0.0392  (0.0004) | 0.0062  (0.0019) | 0.8391  (0.0000) | 0.1286  (0.0000) | 0.0755  (0.0075) | 2 |
| Croatian Kuna | 0.0145  (0.4148) | -0.0269  (0.6107) | 0.0589  (0.0658) | -0.1414  (0.0481) | 0.0010  (0.0673) | 0.9718  (0.0000) | 0.0180  (0.0004) | 0.0155  (0.0079) | 2 |
| Czech Koruna | 0.0263  (0.1005) | -0.0276  (0.4318) | 0.0536  (0.0135) | -0.0580  (0.0350) | 0.0030  (0.0075) | 0.9520  (0.0000) | 0.0393  (0.0000) | 0.0073  (0.4472) | 2 |
| Danish Krone | 0.0184  (0.2657) | -0.0431  (0.4140) | 0.0641  (0.0570) | -0.1583  (0.0399) | 0.0009  (0.0715) | 0.9690  (0.0000) | 0.0219  (0.0001) | 0.0133  (0.0390) | 2 |
| Egyptian Pound | 0.0136  (0.9487) | -0.0495  (0.8831) | 0.0474  (0.4535) | 0.0034  (0.8167) | 0.1852  (0.3556) | 0.7828  (0.0005) | 0.0335  (0.7184) | -0.0245  (0.7744) | 3 |
| Euro | 0.0186  (0.2234) | -0.0436  (0.3946) | 0.0651  (0.0378) | -0.1599  (0.0341) | 0.0009  (0.0869) | 0.9692  (0.0000) | 0.0216  (0.0002) | 0.0136  (0.0356) | 2 |
| Fijian Dollar | 0.0861  (0.0395) | -0.1744  (0.0405) | -0.0341  (0.5669) | 0.0219  (0.7873) | 0.0111  (0.0986) | 0.9277  (0.0000) | 0.1235  (0.1222) | -0.1231  (0.1323) | 4 |
| Gambian Dalasi | -0.0020  (0.8967) | -0.0208  (0.3156) | -0.0457  (0.1822) | 0.0114  (0.2540) | 0.0022  (0.1701) | 0.9725  (0.0000) | 0.0404  (0.0236) | -0.0212  (0.2689) | 2 |
| Ghanaian Cedi | -0.0186  (0.0014) | -0.0618  (0.0064) | -0.0416  (0.0358) | 0.0398  (0.0032) | 0.0036  (0.0030) | 0.8643  (0.0000) | 0.1230  (0.0000) | 0.0355  (0.2274) | 3 |
| Hungarian Forint | -0.0099  (0.6686) | 0.0153  (0.6278) | 0.0077  (0.7014) | -0.0288  (0.0557) | 0.0092  (0.1640) | 0.9454  (0.0000) | 0.0294  (0.0193) | 0.0250  (0.0611) | 3 |
| Indian Rupee | -0.0038  (0.1240) | 0.0413  (0.1483) | -0.0008  (0.9660) | -0.0757  (0.0146) | 0.0004  (0.0045) | 0.8503  (0.0000) | 0.1939  (0.0000) | -0.0391  (0.1210) | 2 |
| Indonesian Rupiah | -0.0078  (0.2102) | -0.0053  (0.8108) | 0.0309  (0.1056) | -0.0041  (0.7283) | 0.0004  (0.2155) | 0.9383  (0.0000) | 0.0555  (0.0132) | 0.0368  (0.0585) | 5 |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model controlling for long memory (cont.)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  | Optimal lag-length |
| Israeli Shekel | 0.0088  (0.3584) | -0.0261  (0.6151) | 0.0190  (0.3703) | -0.0850  (0.1685) | 0.0015  (0.0254) | 0.9405  (0.0000) | 0.0543  (0.0000) | -0.0006  (0.9532) | 4 |
| Japanese Yen | -0.0143  (0.4215) | 0.0388  (0.4392) | 0.0558  (0.0525) | -0.1067  (0.0327) | 0.0082  (0.0166) | 0.9258  (0.0000) | 0.0718  (0.0004) | -0.0361  (0.0739) | 4 |
| Jordanian Dinar | 0.0004  (0.5582) | 0.4253  (0.2884) | -0.0780  (0.0053) | -0.2192  (0.8411) | 0.0000  (0.1180) | 0.9250  (0.0000) | 0.1719  (0.0000) | -0.1459  (0.0000) | 3 |
| Kenyan Shilling | -0.0100  (0.0068) | 0.0342  (0.2726) | -0.0410  (0.0480) | -0.0511  (0.0179) | 0.0016  (0.0791) | 0.8693  (0.0000) | 0.1460  (0.0000) | -0.0160  (0.4734) | 2 |
| Kazakhstan Tenge | -0.0204  (0.0812) | -0.0040  (0.7148) | 0.0189  (0.6423) | 0.0013  (0.7979) | 0.0737  (0.3282) | 0.2969  (0.0789) | 0.2086  (0.0789) | 1.2974  (0.0705) | 4 |
| Kuwaiti Dinar | 0.0017  (0.4507) | 0.1028  (0.3740) | 0.0662  (0.0969) | -0.0110  (0.8014) | 0.0003  (0.2877) | 0.8276  (0.0000) | 0.2575  (0.0086) | -0.0999  (0.4292) | 3 |
| Latvian Lat | 0.0156  (0.0948) | -0.0551  (0.1642) | 0.0484  (0.0221) | -0.1303  (0.0199) | 0.0004  (0.0745) | 0.9666  (0.0000) | 0.0244  (0.0000) | 0.0166  (0.0268) | 2 |
| Lithuanian Lita | 0.0022  (0.4218) | 0.0005  (0.9815) | 0.0599  (0.0275) | -0.1119  (0.0069) | 0.0000  (0.5197) | 0.9216  (0.0000) | 0.0871  (0.0000) | 0.0040  (0.7767) | 2 |
| Malaysian Ringgit | 0.0027  (0.2217) | -0.0234  (0.8220) | 0.0524  (0.0680) | -0.0915  (0.2715) | 0.0002  (0.3822) | 0.9242  (0.0000) | 0.0835  (0.2421) | -0.0004  (0.9838) | 5 |
| Maltese Lira | 0.0218  (0.1553) | -0.0593  (0.2714) | 0.0562  (0.0615) | -0.1509  (0.0620) | 0.0009  (0.0417) | 0.9688  (0.0000) | 0.0213  (0.0002) | 0.0143  (0.0303) | 2 |
| Mauritius Rupee | -0.0117  (0.0074) | 0.0478  (0.1535) | 0.0591  (0.0131) | 0.0274  (0.4864) | 0.0001  (0.3369) | 0.8988  (0.0000) | 0.1465  (0.0000) | -0.0449  (0.0567) | 3 |
| Mexican Peso | 0.0015  (0.8764) | -0.0363  (0.1318) | -0.0029  (0.8750) | -0.0241  (0.0100) | 0.0032  (0.0109) | 0.9198  (0.0000) | 0.0436  (0.0026) | 0.0619  (0.0003) | 3 |
| Moroccan Dirham | 0.0194  (0.0778) | -0.0766  (0.1528) | 0.0518  (0.0523) | -0.1542  (0.0925) | 0.0005  (0.0771) | 0.9689  (0.0000) | 0.0261  (0.0002) | 0.0060  (0.4029) | 2 |
| N. Zealand Dollar | 0.0005  (0.9776) | 0.0149  (0.6147) | 0.0078  (0.7165) | -0.0306  (0.1546) | 0.0045  (0.0018) | 0.9593  (0.0000) | 0.0206  (0.0001) | 0.0245  (0.0010) | 3 |
| Nigerian Naira | -0.0033  (0.8155) | -0.0193  (0.0064) | -0.0158  (0.8108) | -0.0008  (0.3549) | 0.1346  (0.2621) | 0.5944  (0.0000) | 0.1517  (0.1904) | 0.2743  (0.3596) | 3 |
| Norwegian Krone | 0.0064  (0.7379) | -0.0038  (0.9218) | 0.0319  (0.1767) | -0.0645  (0.0204) | 0.0032  (0.0054) | 0.9609  (0.0000) | 0.0295  (0.0000) | 0.0074  (0.3842) | 5 |
| Peruvian Sol | 0.0049  (0.2056) | -0.0237  (0.5718) | 0.0291  (0.2080) | 0.0205  (0.6566) | 0.0006  (0.1561) | 0.8567  (0.0000) | 0.1351  (0.0434) | 0.0746  (0.1104) | 4 |
| Philippine Peso | -0.0045  (0.6501) | 0.0184  (0.7662) | -0.0286  (0.2042) | 0.0757  (0.0839) | 0.0016  (0.6508) | 0.9417  (0.0000) | 0.0582  (0.4183) | -0.0151  (0.4908) | 6 |
| Polish Zloty | 0.0280  (0.1185) | -0.0302  (0.3025) | 0.0660  (0.0006) | -0.0385  (0.0086) | 0.0068  (0.0105) | 0.9308  (0.0000) | 0.0457  (0.0000) | 0.0257  (0.1099) | 2 |
| Qatari Rial | -0.0005  (0.5898) | 1.4125  (0.0706) | -0.0481  (0.0615) | -2.4208  (0.4352) | 0.0002  (0.2149) | 0.4961  (0.0005) | 0.1798  (0.0383) | 0.1142  (0.3213) | 4 |
| Romanian Leu | -0.0527  0.0000 | 0.0719  (0.0000) | 0.0315  (0.0380) | -0.0391  (0.0014) | 0.0002  (0.1904) | 0.9341  (0.0000) | 0.0836  (0.0000) | -0.0226  (0.1118) | 2 |
| Russian Rouble | -0.0061  (0.0881) | -0.0067  (0.5776) | 0.0240  (0.1589) | -0.0041  (0.0376) | 0.0003  (0.0176) | 0.9096  (0.0000) | 0.0795  (0.0000) | 0.0408  (0.0089) | 4 |
| Singapore Dollar | 0.0130  (0.1181) | -0.0733  (0.3873) | 0.0290  (0.2468) | -0.2697  (0.0722) | 0.0010  (0.0004) | 0.9453  (0.0000) | 0.0356  (0.0000) | 0.0214  (0.0288) | 3 |
| Slovak Koruna | 0.0064  (0.7490) | 0.0083  (0.8768) | 0.0801  (0.0163) | -0.1645  (0.0230) | 0.0011  (0.1244) | 0.9715  (0.0000) | 0.0178  (0.0002) | 0.0164  (0.0121) | 2 |
| Slovenian Tolar | 0.0160  (0.3342) | -0.0425  (0.4085) | 0.0654  (0.0500) | -0.1565  (0.0461) | 0.0010  (0.0823) | 0.9697  (0.0000) | 0.0219  (0.0000) | 0.0116  (0.0426) | 2 |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5: Maximum likelihood estimates from the original Sentana and Wadhwani (1992) model controlling for long memory (cont.)** | | | | | | | | | |
|  |  |  |  |  |  |  |  |  | Optimal lag-length |
| Sri Lankan Rupee | -0.0038  (0.0963) | -0.1352  (0.0004) | -0.0080  (0.8433) | 0.0535  (0.0042) | 0.0016  (0.0989) | 0.6395  (0.0000) | 0.3562  (0.0013) | 0.4928  (0.1934) | 3 |
| S. African Rand | -0.0353  (0.1027) | 0.0229  (0.2856) | 0.0037  (0.8445) | -0.0174  (0.0247) | 0.0131  (0.0057) | 0.9268  (0.0000) | 0.0446  (0.0000) | 0.0352  (0.0033) | 2 |
| S. Korean Won | 0.0103  (0.2705) | -0.0061  (0.8668) | 0.0187  (0.2502) | -0.0170  (0.0275) | 0.0035  (0.0001) | 0.9187  (0.0000) | 0.0493  (0.0000) | 0.0394  (0.0029) | 3 |
| Swedish Krona | 0.0039  (0.8619) | -0.0017  (0.9710) | 0.0334  (0.2233) | -0.0787  (0.0508) | 0.0032  (0.0043) | 0.9627  (0.0000) | 0.0227  (0.0025) | 0.0167  (0.0333) | 2 |
| Swiss Franc | 0.0547  (0.0015) | -0.0710  (0.0158) | -0.0321  (0.2950) | 0.0046  (0.7129) | 0.0025  (0.1571) | 0.9628  (0.0000) | 0.0094  (0.4926) | 0.0596  (0.0269) | 3 |
| Taiwan New Dollar | 0.0109  (0.0199) | -0.1765  (0.0471) | 0.0323  (0.2594) | -0.4577  (0.0664) | 0.0012  (0.0187) | 0.8912  (0.0000) | 0.0878  (0.0002) | 0.0184  (0.3569) | 3 |
| Tanzanian Shilling | -0.0063  (0.0473) | -0.0166  (0.3228) | 0.0484  (0.0281) | -0.0131  (0.0000) | 0.0007  (0.0188) | 0.8223  (0.0000) | 0.2095  (0.0000) | 0.0298  (0.2405) | 2 |
| Thai Baht | 0.0156  (0.0003) | -0.0555  (0.1503) | 0.0390  (0.0171) | -0.0103  (0.0077) | 0.0049  (0.0002) | 0.7847  (0.0000) | 0.1996  (0.0000) | -0.0290  (0.4599) | 3 |
| Tunisian Dinar | -0.0149  (0.1309) | -0.0041  (0.8759) | 0.0119  (0.4625) | -0.0215  (0.0927) | 0.0019  (0.0921) | 0.9526  (0.0000) | 0.0207  (0.0597) | 0.0450  (0.0006) | 4 |
| Turkish Lira | 0.0538  (0.0045) | -0.1685  (0.0000) | 0.0184  (0.3797) | 0.0073  (0.0016) | -0.0007  (0.6880) | 0.9956  (0.0000) | -0.0262  (0.0000) | 0.0629  (0.0000) | 2 |
| UK Pound | 0.0262  (0.1021) | -0.0778  (0.0697) | 0.0123  (0.3915) | -0.0512  (0.0006) | 0.0026  (0.0249) | 0.9402  (0.0000) | 0.0506  (0.0124) | 0.0050  (0.7462) | 2 |
| Ukrainian Hryvnia | -0.0050  (0.0892) | -0.0097  (0.3513) | -0.1062  (0.0021) | 0.0000  (0.9260) | 0.0002  (0.0978) | 0.8325  (0.0000) | 0.1753  (0.0000) | 0.1959  (0.1120) | 3 |
| Uruguayan Peso | -0.0010  (0.8965) | -0.0245  (0.3521) | 0.0022  (0.9312) | -0.0042  (0.0942) | 0.0034  (0.4411) | 0.9251  (0.0000) | 0.0615  (0.1095) | 0.0398  (0.2465) | 3 |
| Ugandan New Shilling | -0.0132  (0.0022) | -0.0057  (0.7330) | 0.0243  (0.3972) | -0.0251  (0.0009) | 0.0023  (0.0603) | 0.8180  (0.0000) | 0.2060  (0.0000) | 0.0241  (0.5485) | 2 |
| Vanuatu Vatu | -0.0076  (0.4309) | 0.0455  (0.3360) | 0.0238  (0.1719) | 0.0032  (0.9302) | 0.0018  (0.0100) | 0.9660  (0.0000) | 0.0121  (0.1591) | 0.0264  (0.0026) | 6 |
| Zambian Kwacha | -0.0277  (0.0167) | 0.0148  (0.2238) | 0.0121  (0.5585) | -0.0043  (0.0311) | 0.0121  (0.0128) | 0.8421  (0.0000) | 0.2027  (0.0000) | -0.0405  (0.2410) | 5 |
| The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (29/12/2000- 31/5/2018) | | | | | | | | | |
|  | | | | | | | | | |
|  | | | | | | | | | |
| The *n* (*n = 2, 3, 4, …*) here pertains to the lag-length, whose optimal value (inferred via a grid-search) which maximizes the value of the likelihood function is depicted in the right-most column of the table. Parentheses include p-values. | | | | | | | | | |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 6: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for the global financial crisis** | | | | | |
|  |  |  |  |  |
| Albanian Lek | 0.0276  (0.7122) | -0.0077  (0.8008) | 0.0333  (0.7279) | -0.0756  (0.3654) |
| Algerian Dinar | -0.3612  (0.0038) | -0.1958  (0.0000) | 0.2198  (0.0977) | -0.0662  (0.0698) |
| Argentine Peso | 0.2125  (0.0213) | -0.1447  (0.2655) | -0.0148  (0.8374) | 0.0002  (0.8438) |
| Australian Dollar | -0.0245  (0.7264) | 0.0038  (0.8845) | -0.0001  (0.9934) | -0.0378  (0.3544) |
| Bangladeshi Taka | -1.3498  (0.0212) | -0.2200  (0.0050) | 0.7248  (0.2841) | 0.0108  (0.4321) |
| Botswanan Pula | -0.1036  (0.2084) | -0.0730  (0.0066) | 0.0697  (0.1986) | 0.0014  (0.7818) |
| Brazilian Real | -0.0485  (0.4643) | -0.0294  (0.1723) | -0.0056  (0.5780) | -0.0095  (0.1335) |
| Brunei Dollar | 0.1253  (0.2284) | 0.0347  (0.1281) | -0.4508  (0.3051) | -0.3671  (0.0110) |
| Bulgarian Lev | 0.0214  (0.7795) | 0.0342  (0.2693) | 0.0360  (0.6706) | -0.1190  (0.1064) |
| Canadian Dollar | -0.0074  (0.9237) | 0.0254  (0.3811) | 0.0304  (0.5086) | -0.1137  (0.1260) |
| Benin CFA (Franc) | 0.0197  (0.7958) | 0.0381  (0.1999) | 0.0364  (0.6451) | -0.1274  (0.0557) |
| Chilean Peso | 0.2103  (0.0211) | -0.0013  (0.9671) | -0.0584  (0.2792) | 0.0087  (0.8805) |
| Chinese Yuan | 0.0347  (0.8613) | -0.1094  (0.2949) | -3.1171  (0.6822) | 1.1080  (0.6360) |
| Colombian Peso | 0.0580  (0.4654) | 0.0756  (0.0000) | -0.0118  (0.4246) | -0.0063  (0.0852) |
| Croatian Kuna | -0.0122  (0.8621) | 0.0408  (0.1876) | 0.0581  (0.4318) | -0.1202  (0.0722) |
| Czech Koruna | 0.0951  (0.2536) | 0.0187  (0.4443) | -0.0307  (0.5395) | -0.0217  (0.4394) |
| Danish Krone | 0.0251  (0.7508) | 0.0368  (0.2220) | 0.0337  (0.6690) | -0.1251  (0.0765) |
| Egyptian Pound | -0.1741  (0.0365) | -0.2429  (0.0011) | -0.3298  (0.8174) | -0.0004  (0.5378) |
| Euro | 0.0197  (0.7979) | 0.0380  (0.2149) | 0.0363  (0.6480) | -0.1273  (0.0638) |
| Fijian Dollar | -0.2947  (0.1718) | -0.3802  (0.0198) | 0.1300  (0.5479) | 0.3509  (0.3877) |
| Gambian Dalasi | -0.4750  (0.0000) | -0.1923  (0.0000) | 0.0312  (0.2579) | 0.0249  (0.0075) |
| Ghanaian Cedi | -0.3299  (0.0001) | -0.3389  (0.0000) | 0.0574  (0.2248) | 0.0725  (0.0000) |
| Hungarian Forint | -0.0479  (0.6540) | 0.0305  (0.3121) | 0.0308  (0.3132) | -0.0573  (0.0427) |
| Indian Rupee | 0.1873  (0.0195) | 0.0153  (0.4433) | -0.2472  (0.0015) | -0.0253  (0.4340) |
| Indonesian Rupiah | -0.0053  (0.9551) | 0.0652  (0.0341) | -0.0129  (0.5554) | -0.0170  (0.4728) |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 6: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for the global financial crisis (continued)** | | | | |
|  |  |  |  |  |
| Israeli Shekel | -0.0192  (0.8697) | 0.0533  (0.0898) | 0.0396  (0.6634) | -0.0519  (0.6530) |
| Japanese Yen | 0.0057  (0.9583) | 0.0421  (0.2497) | -0.0928  (0.2259) | -0.1066  (0.1550) |
| Jordanian Dinar | -0.4726  (0.0504) | -0.3963  (0.0000) | 7.1324  (0.7303) | -1.1132  (0.5386) |
| Kenyan Shilling | 0.1760  (0.0186) | -0.0233  (0.3128) | -0.0780  (0.0207) | 0.0776  (0.1715) |
| Kazakhstan Tenge | -0.2368  (0.0500) | 0.1402  (0.0232) | -0.0010  (0.5103) | -0.0016  (0.1237) |
| Kuwaiti Dinar | -0.0652  (0.4117) | -0.1519  (0.0000) | -0.1989  (0.3201) | -0.1523  (0.0725) |
| Latvian Lat | 0.0264  (0.7159) | 0.0346  (0.1613) | 0.0225  (0.7610) | -0.1193  (0.0528) |
| Lithuanian Lita | 0.0331  (0.6408) | 0.0085  (0.8028) | 0.0113  (0.8035) | -0.0431  (0.4379) |
| Malaysian Ringgit | 0.2424  (0.0090) | -0.0444  (0.3770) | -0.7906  (0.0159) | 0.0294  (0.7338) |
| Maltese Lira | 0.0196  (0.7927) | 0.0242  (0.3755) | 0.0359  (0.6366) | -0.0994  (0.1529) |
| Mauritius Rupee | -0.0515  (0.7247) | -0.2259  (0.0000) | -0.1106  (0.4221) | 0.0625  (0.0629) |
| Mexican Peso | 0.0188  (0.7739) | 0.0127  (0.4841) | -0.0268  (0.1258) | 0.0296  (0.0673) |
| Moroccan Dirham | -0.0010  (0.9898) | -0.0103  (0.6841) | 0.0737  (0.5475) | -0.0604  (0.4624) |
| N. Zealand Dollar | -0.0169  (0.8188) | 0.0653  (0.0167) | 0.0262  (0.2558) | -0.0760  (0.0179) |
| Nigerian Naira | 0.3673  (0.5396) | -0.0801  (0.3274) | 0.0230  (0.7054) | 0.0009  (0.7068) |
| Norwegian Krone | 0.0337  (0.6526) | 0.0708  (0.0053) | -0.0417  (0.3368) | -0.0844  (0.0079) |
| Peruvian Sol | -0.2735  (0.0001) | -0.0180  (0.5528) | 0.1734  (0.0584) | -0.1659  (0.0172) |
| Philippine Peso | -0.0477  (0.5911) | -0.0965  (0.0000) | -0.1533  (0.1116) | -0.0227  (0.3112) |
| Polish Zloty | 0.1065  (0.1337) | 0.0643  (0.0037) | -0.0025  (0.9202) | -0.0484  (0.0447) |
| Qatari Rial | -0.2457  (0.0026) | -0.3737  (0.0000) | -77.1752  (0.3558) | 1.0111  (0.7699) |
| Romanian Leu | 0.1154  (0.0968) | 0.0197  (0.3693) | -0.0117  (0.6666) | -0.0673  (0.014) |
| Russian Rouble | 0.0685  (0.2268) | 0.0553  (0.0027) | 0.0434  (0.0455) | -0.0060  (0.2405) |
| Singapore Dollar | -0.0157  (0.8662) | 0.0097  (0.6838) | 0.0286  (0.9326) | -0.2424  (0.1048) |
| Slovak Koruna | 0.0817  (0.4047) | 0.0548  (0.1038) | -0.0031  (0.9718) | -0.1384  (0.0536) |
| Slovenian Tolar | 0.0199  (0.7870) | 0.0264  (0.3921) | 0.0371  (0.6276) | -0.1008  (0.1406) |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 6: Maximum likelihood estimates from the Sentana and Wadhwani (1992) model controlling for the global financial crisis (continued)** | | | | |
|  |  |  |  |  |
| Sri Lankan Rupee | 0.0052  (0.9515) | 0.0122  (0.7900) | -0.0701  (0.2150) | -0.0382  (0.0052) |
| S. African Rand | 0.0455  (0.4572) | 0.0522  (0.0837) | 0.0044  (0.7958) | -0.0198  (0.2716) |
| S. Korean Won | 0.1277  (0.1314) | -0.0193  (0.3480) | -0.0163  (0.0080) | -0.0278  (0.5244) |
| Swedish Krona | -0.0340  (0.5997) | 0.0286  (0.3207) | 0.0173  (0.6845) | -0.0574  (0.1987) |
| Swiss Franc | -0.0668  (0.6526) | -0.0515  (0.0322) | 0.0542  (0.7284) | -0.0040  (0.8489) |
| Taiwan New Dollar | 0.4361  (0.0004) | 0.1197  (0.0001) | -1.8027  (0.0023) | -0.9584  (0.0009) |
| Tanzanian Shilling | 0.2304  (0.0013) | -0.1129  (0.0000) | -0.0259  (0.1761) | 0.0022  (0.5300) |
| Thai Baht | 0.3386  (0.0031) | 0.0426  (0.0353) | -1.3165  (0.0038) | -0.0144  (0.0165) |
| Tunisian Dinar | -0.0311  (0.7656) | -0.1183  (0.0000) | 0.0484  (0.7989) | -0.1618  (0.0000) |
| Turkish Lira | -0.1657  (0.0188) | -0.0230  (0.2909) | 0.1010  (0.0000) | 0.0139  (0.0000) |
| UK Pound | -0.2229  (0.0057) | 0.0009  (0.9629) | 0.2155  (0.0034) | 0.0282  (0.2389) |
| Ukrainian Hryvnia | -0.2767  (0.0006) | -0.1868  (0.0000) | 0.0032  (0.1049) | 0.0000  (0.9583) |
| Uruguayan Peso | 0.0148  (0.8803) | -0.0258  (0.6549) | 0.0321  (0.6884) | -0.0057  (0.3144) |
| Ugandan New Shilling | 0.0562  (0.3863) | -0.0392  (0.2065) | 0.0044  (0.7537) | 0.0073  (0.4282) |
| Vanuatu Vatu | -0.2645  (0.0010) | 0.0289  (0.1854) | 0.0825  (0.1719) | -0.3652  (0.0000) |
| Zambian Kwacha | 0.0939  (0.1139) | -0.0017  (0.9355) | -0.0055  (0.0119) | 0.0073  (0.0113) |
| The table presents the maximum likelihood estimates of the autocorrelation and feedback parameters from the following equations for the full sample period (29/12/2000- 31/5/2018):  Dt =1, for the 10/10/2007 – 6/3/2009 period, zero otherwise. Parentheses include p-values. | | | | |

1. High frequency algorithms include a series of commands based primarily on price and volume parameters, allowing for very low latency (i.e. very short time lapsing between order-submission and -execution), as low as a few milliseconds (Hasbrouck and Saar, 2013). [↑](#footnote-ref-1)
2. All exchange rate quotes are direct ones as per each currency’s home market versus the US dollar, i.e. the US dollar is the base currency in this case and the home currency is the counter currency (as also implied in Aguirre and Saidi, 1999 and Laopodis, 2005). For example, with regards to the Euro, its value versus the US dollar at the end-date of our sample window (31/5/2018) was 0.8567 (or, more formally, USD/EUR = EUR 0.8567, i.e. 1 US dollar was equal to 0.8567 Euros). Given the above, increasing (decreasing) values for our quotes suggest the US dollar has appreciated (depreciated) versus the home currency, or, equivalently, depreciation (appreciation) for the home currency. [↑](#footnote-ref-2)
3. Based on the previous footnote, this indicates that 36 (30) currencies depreciated (appreciated) in value, on average, versus the US dollar during our sample period. [↑](#footnote-ref-3)
4. To elaborate on this with an example, assume the following USD/EUR quotes (in brackets) for the following dates: 28/5/2018 (0.8605), 29/5/2018 (0.8648) and 30/5/2018 (0.8611). These quotes suggest that the Euro depreciated on the 29/5/2018 and appreciated on the 30/5/2018. The log-differenced return of the USD/EUR exchange rate series in this case would be positive for the 29/5/2018 and negative for the 30/5/2018; as a result, positive feedback traders would buy (sell) Euros on the 29/5/2018 (30/5/2018), i.e. when the Euro has depreciated (appreciated) against the US dollar, while negative feedback traders would be performing the exact opposite (selling Euros on the 29/5/2018 and buying Euros on the 30/5/2018). [↑](#footnote-ref-4)
5. Since positive feedback traders buy (sell) a currency when it depreciates (appreciates), their trades are conducive to (or reflective of their faith in) the currency’s sustainability when it depreciates (they expect, for example, the central bank to support the currency), yet not when it appreciates (they expect its appreciation to reverse). This, in turn, suggests that positive feedback traders would tend to buy undervalued and sell overvalued currencies, thus contributing to stability in currency markets. On the other hand, negative feedback traders can destabilize a currency by buying (selling) it when it appreciates (depreciates) as this can help perpetuate its appreciation (depreciation) and, hence, its deviation from its long-run valuations. For a detailed discussion of the above, see Aguirre and Saidi (1999) and Laopodis (2005). [↑](#footnote-ref-5)
6. Currency appreciations are reflected through negative -values, hence, if and is significantly positive, this would indicate there would be stronger positive feedback trading (as there would be stronger negative autocorrelation in returns). [↑](#footnote-ref-6)
7. This approach is in line with that followed by Antoniou et al. (2011) to test for long memory in feedback trading; we thank an anonymous referee for suggesting it. [↑](#footnote-ref-7)
8. Statistical significance in this study is established at the 10 percent significance level (i.e. for p-values < 0.1). [↑](#footnote-ref-8)
9. Campbell et al. (1993), for example, demonstrated how lower volumes can give rise to stronger autocorrelation in returns. [↑](#footnote-ref-9)
10. As the 20 currencies with a significant entail insignificant, in most cases, -values, this raises the issue of proper interpretation of . Given that ϕ1 = - κγ, we therefore need to assess whether the significance of is due to the significance of γ. Similar to Koutmos (2012), we assess this drawing on the approach outlined by Kmenta (1986, pp. 485-490) to generate standard errors for the γ-coefficient and then gauge the significance of γ (whose value, by construction, equals *-ϕ1 /κ* for each currency). We find that γ is significant for all of those 20 currencies; results are not presented here in the interest of brevity and are available from the authors on request. [↑](#footnote-ref-10)
11. It is important to note here that Equation (2) draws on a single feedback coefficient, without discriminating between the demand of positive and that of negative feedback traders in feedback traders’ demand function. It is entirely plausible, for example, that a currency entails both significant positive and negative feedback trading and at the same time reveal either a) a significantly negative (positive) , if positive (negative) feedback trading is stronger than negative (positive) feedback trading or b) an insignificant , if the two feedback trader-types cancel each other out. As a result, one needs to take the above into account when interpreting the results in the context of the Sentana and Wadhwani (1992) model; we thank an anonymous referee for raising this issue. [↑](#footnote-ref-11)
12. See also the discussion in the previous footnote; of course, in theory, it is equally possible that is insignificant simply because of the lack of feedback traders. [↑](#footnote-ref-12)
13. In the case of the Fijian Dollar, is insignificant and is significantly positive – the sole currency with a significantly positive -value, as mentioned; in this currency’s case, appreciations prompt stronger positive feedback trading (i.e. selling), possibly due to traders not viewing the appreciation as sustainable in the long run. [↑](#footnote-ref-13)
14. The -coefficient is significantly positive in 28 of the 66 currencies. [↑](#footnote-ref-14)
15. The first-order autocorrelation coefficient appears more significant (26 cases) for appreciations than depreciations (16 cases), with its sign being negative in the majority of those cases. [↑](#footnote-ref-15)
16. Of course, there are 20 currencies for which the likelihood function is maximized at a certain higher order of lags, without feedback trading being present, as results in Table 5 illustrate. [↑](#footnote-ref-16)
17. Most evidence of first-order autocorrelation surfaces in-crisis (23 cases), as opposed to outside it (12 cases); negative autocorrelation appears in 10 (5) cases inside (outside) the crisis, with the rest of the cases referring to positive autocorrelation. Overall, with the exception of the Norwegian Krone and the UK Pound, the rest of the currencies presenting any evidence of significant autocorrelation emanate from emerging/frontier markets. [↑](#footnote-ref-17)