Order Flow and Exchange Rate Dynamics:
An Application to Emerging Markets

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JLE: F31,
Keywords: Order Flow, Foreign Exchange Markets, Exchange Rates, Forex Microstructure

April 2010

Abstract

The paper examines short-run exchange rate dynamics in an emerging market based on the recent microstructure framework of foreign exchange markets where the main explanatory variable is the order flow of end-user customers. The study makes two main contributions to the literature. First, it modifies the model to take account of a unique feature of the majority of emerging markets, namely the existence of a black market for FOREX. Secondly, it uses a unique database covering almost the complete Ghanaian market, and for a long time span compared to previous studies, which typically use data for a single market-maker and for a short period of time. The study confirms the contemporaneous relationship between flows and exchange rates suggested by the previous literature (Evans and Lyons, 2002a) but it also finds a lagged interaction between order flow and exchange rates, which could be due to the delays in the price transmission, which are associated with market inefficiencies. Order flow impacts on exchange rates through the official market, while its impact on the black market is only temporary. Additionally, the study confirms the connection between the price impact of the order flow and the degree of liquidity in the FX market.

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Acknowledgement: We would like to thank the participants of the Exchange rates and Capital Flows Conference, at the Bank of England in 2007 and 2008 and the Brazilian Finance Association in 2009. We would also like to thank the Emerging Markets Group, Cass Business School in London for financial support.

1. Introduction

This study tries to explain the behaviour of the exchange rate in an emerging market, namely Ghana, based on the recent microstructure framework of foreign exchange markets. This is one of the very few studies to apply such a framework to an emerging market.[1] One key premise of the microstructure approach is the explanatory role of the order flow in the behaviour of the exchange rate. The study uses a unique database, which covers over 80% of the customer order flow of the Ghanaian FX market.[2] This is in contrast to previous studies, such as Evans and Lyons (2002a), and Marsh and O'Rourke (2005) that use data for a single market-maker and often for a short period of time. In addition, the longer time span also allows for a more precise estimation of the impact of order flow on weekly exchange rate movements. Furthermore, the study takes into account a unique feature of the majority of emerging markets, namely the existence of a black market for foreign exchange. Thus, we consider the interaction of the black market and order flow, and black market and official market, in addition to the interaction between the official rate and order flow. The black market is thus an additional channel for disseminating public and/or private information.

The paper is structured as follows. Section 2 reviews the literature. Section 3 provides the main characteristics of the Ghanaian FX market and their impact on the role of order flow as a transmission mechanism for private information. Section 4 presents the data and methodology. Section 5 reports the empirical evidence, while Section 6 summarises and concludes the paper.

2. Review of the literature

Foreign exchange microstructure research has been motivated by the need to understand exchange rate dynamics at short horizons.[3] The dominant exchange rate models of the recent decades take a macro perspective and come from the macro modelling tradition and have some relative value at long horizons. The search to find a new framework to explain short-run exchange rate dynamics has led to the micro-structural approach to exchange rates, which takes into account the currency trading process. These micro-based models set out to model the structure of the foreign exchange market in a more

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[1] The only two other studies on emerging markets are Wu (2006) for Brazil and Gereben, et al. (2006) for Hungary.

[2] The data were provided through contacts at the Central Bank of Ghana.

[3] For a survey of the theoretical and empirical literature see Osler (2009).

realistic manner. In this setting, information is dispersed and heterogeneous agents have different information sets. The trading process itself is not transparent and agents may have access to private information about fundamentals or non-fundamental variables that can be exploited in the short-run. Consequently the transactions of better-informed agents may have a larger effect on exchange rates than those of uninformed agents. Thus, the microstructure approach not only recognises private information as being important for exchange rate determination but also takes into account how differences between agents and trading mechanisms affect exchange rates. (see Evans and Lyons, 2002a). This is in contrast to macro models, which assume that all relevant information is commonly known and all participants are the same.[4]

Thus, one of the most important explanatory variables in the microstructure approach to exchange rates is order flow. Order flow, as defined by Evans and Lyons (2002a) refers to "net of buyer-initiated and seller initiated orders; it is a measure of net buying pressure." Order flow consists of 'signed' transaction volumes. When a participant initiates a transaction by selling the base currency in exchange for foreign currency, the order has a negative sign. On the contrary, if participants buy foreign currency in exchange for base currency, the order has a positive sign.

By observing order flow, a participant might be able to have an idea of the sort of information others may hold. For example, if an initiator's expectation is that the base currency will fall, this may lead to a sale of the base currency in exchange for the foreign currency. This order flow will, thus, provide vital information to other participants and might result in the strengthening of the foreign currency. Order flow is viewed as a transmission mechanism through which information is transmitted to price. The extent to which order flow is informative depends on the factors that cause it. It is most informative when it transmits private information about macroeconomic fundamentals that is scattered among agents. By aggregating information in this way, order flow establishes a connection between macroeconomic fundamentals and exchange rate movements. On the other hand, order flow is less informative when it is as a result of inventory control activities in reaction to liquidity shocks. Nevertheless, the importance of order flow in exchange rate determination does not mean that it is the underlying cause of exchange rate movements. Rather it is a proximate cause with information being the underlying cause. The problem then lies in identifying what information determines order flow.

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[4] Earlier works on FX microstructure have used surveys of FX market participants to support strong heterogeneity of expectations and an increasing diffusion of expectations.

The relatively impressive explanatory power of order flow has been confirmed by several microstructure studies. For example, Evans and Lyons (2002a) propose a transaction frequency model called the 'portfolio shifts model' which focuses on the information content of order flow. It is a hybrid model which combines both micro and macro variables. A unique feature of the model is that it allows the use of daily frequency data. According to this model daily exchange rate movements depend on signed order flow and changes in the interest rate differential. Under the model's null hypothesis, causality runs strictly from order flow to price. The change in interest differential is preferred to other macro determinants because its data is available at a daily frequency and it is usually the main variable in exchange rate determination models.[5] Using interdealer data from Reuters Dealing 2000-1 to analyse the contemporaneous relationship between order flow and exchange rate movements for the DM/USD and JPY/USD over the period between May 1st and August 31st 1996, they find the order flow coefficient to be significant and positively (correctly) signed for both exchange rate equations. This means that net dollar purchases leads to an increase in DM and JPY prices of dollars. The model explains about 64% and 46% of movements in the DM/USD and YEN/USD respectively. More specifically these exchange rate movements are mainly due to order flow, while changes in interest rates account for very little. The paper concludes that a net order flow of $1bn leads the USD to appreciate by 0.5%.

This contemporaneous relationship between order flow and the exchange rate has been confirmed in other studies and for different currency order flow combinations. For example, for the deutschmark see Lyons (2001), Payne (2003); for the Euro see Breedon and Vitale (2004) and Berger et al. (2006), for the Japanese Yen see Evans and Lyons (2002a); for the British sterling see Berger et al. (2006); and for several other European currencies see Evans and Lyons (2002b) and Rime (2001). Another group of studies examine the information content of disaggregated order flow.[6] They find that financial customer order flow is positively correlated with exchange rate movements, whilst non-financial customer order flow is negatively correlated. They interpret these results that financial customer flows contain price relevant information with non-financial customers following negative feedback trading rules.

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[5] We should expect a positively signed interest differential where the interest rate differential is the nondollar interest rate minus the US interest rate.
[6] See e.g. Carpenter and Wang (2004), Froot and Ramadorai (2005), Evans and Lyons (2005), Marsh and O'Rourke (2005).

Because of the strict causality running from order flow to price, the above empirical models do not allow for the case where exchange rate movements could cause order flow (feedback effects). In the presence of feedback effects, the coefficient estimate of order flow is biased and the results from the model could be misleading. The possibility of feedback trading rules was taken into account in Payne (2003) by applying a simple VAR methodology introduced in Hasbrouck (1991). This linear VAR model consists of trades and quote revisions. The dataset covers all interdealer trades transacted through the Reuters Dealing 2000-2 system in the spot USD/DEM market over the week spanning October 6th to October 10th 1997. The results show that order flow is a fundamental determinant of exchange rate movements even if one takes into account feedback trading.

Danielsson and Love (2004) also examine the issue of feedback trading, but their paper looks at contemporaneous feedback trading and its effect on the informativeness of order flow. Thus, the VAR specification differs from that of Payne 2003 in that order flow is allowed to depend on current exchange rate returns. Using brokered interdealer data for the spot USD/EUR, they find that when contemporaneous feedback trading is allowed, the impact of order flow shock is larger compared to the previous case.

The key question addressed in this paper is: Do the main results from the microstructure approach to modelling advanced FX markets also hold for emerging FX markets? There are only a couple of studies which have examined the role of order flow in emerging FX markets. One of those is Wu (2006) which studies the behaviour of order flow and its influence on the official exchange rate dynamics in Brazil, using data of daily customer transactions over the period July 1999 to June 2003, which represents 100% of the official Brazilian market. Customers are further divided into commercial customers, financial customers and central bank. Wu's model is similar to that of previous microstructure models but with two key changes. First, Wu favours a general equilibrium model where customers' demand for FX is induced by macro fundamentals, including contemporaneous changes in the exchange rate. Secondly, unlike Evans and Lyons model, FX dealers do not have to close with zero net positions at the end of each trading day. These dealers may decide to provide extra liquidity in the case where there is an imbalance between customer buy and sell orders, but they charge a risk premium, which causes the domestic currency to depreciate. The model also allows/predicts a two-way relationship between customer order flow and exchange rates, which is confirmed by their results.

Gereben et al. (2006) examine the role of customer order flow in the Hungarian forint (EUR/HUF) market. Their study is mainly based on the Evans and Lyons (2002a) framework. Not only do they test whether customer order flow contributes to explaining exchange rate but they also identify the roles played by the different customer types for which they have data for (domestic non-market making banks, domestic non-banks, the central bank, foreign banks and foreign non-banks). Using maximum likelihood they estimate a generic model at a daily frequency where all the different order flow variables are included,

Results indicate that the estimated coefficients of the foreign banks', foreign non-banks' and central bank's order flow are negative and significant, implying that purchases of domestic currency by these customers cause an appreciation in the Hungarian currency relative to the euro, while the coefficients of the domestic bank and non-banks are not significant.

In our study we start with the basic model of Evans and Lyons (2002a) and modify it to take account on the one hand, of market inefficiencies and on the other hand, of the existence of black market. The black market for FOREX is a widespread phenomenon in emerging markets. The paper using proprietary data covering almost the whole market confirms the importance of order flow in explaining short-run exchange rate dynamics. The study confirms the contemporaneous relationship (between order flows and exchange rates as suggested by previous studies. However, we also observe a lagged interaction between order flow and exchange rates. These lagged effects could be due to the delays in the price transmission which are associated with inefficiencies related to the aggregation of private information due to the characteristics of the Ghanaian FX market. Order flow impacts on exchange rates through the official market, while its impact on the black market is only temporary. Additionally, the study confirms the connection between the price impact of the order flow and the degree liquidity in the FX market.

3. Main Characteristics of the Ghanaian FX market

Between January to August 2007, average daily market turnover in the Ghanaian FX market was approximately $38m. It is a spot market with no forward FX market. The central bank is the main supplier of FX with its main source being export receipts, donor inflows, taxes and royalties. Unlike the major currencies (with liquid markets) that are traded worldwide, a small currency like the Cedi, the Ghanaian currency, is only traded onshore in Ghana.[7] The US dollar is the most traded foreign currency in Ghana and subsequently plays the role of a vehicle currency in cross currency transactions.

The black market for foreign exchange in Ghana came to existence for a number of reasons. In early 1980s the black market was thriving due to smuggling and illegal FX operations.[8] In 1981 the FX operations had become so widespread that the black market rate was 9.6 times higher than the official rate. Around this period, transactions in the black economy accounted for about a third of Ghana's GDP. [9] In 1986, however, the government introduced a system where the exchange rate was determined by periodic currency auctions, which were under the influence of market forces and consisted of a two-tier exchange rate system, one rate for essentials and another for non-essentials. By 1987, the two auctions were merged. Most of the foreign exchange inflows were allocated through the auctions. In an attempt to eradicate black market operations, the government allowed private foreign-exchange bureaus (thereafter FX bureaus) to trade in foreign currency. In July 1989, there were 148 FX bureaus operating all over Ghana. Eventually the huge gap between the auction rate and FX bureau rate narrowed drastically. Specifically, the gap narrowed from 29% in 1988 to about 6% in 1991. In 1992, the auction system was abandoned. FX bureaus and other purchasers of foreign currency were referred to the central bank, which used the market-determined exchange rate. Gradually Ghana moved towards a market-determined exchange rate and lowered tariffs in order to attract more trade. In this study we use the FX bureaus rate as a proxy for the black market rate.

Only licensed banks and foreign exchange bureaus are allowed to perform FX intermediation. In Ghana, all the banks (both domestic and foreign-owned) are permitted to deal in FX. The licensing of intermediaries makes it easier for the central bank to enforce its regulations concerning the use and exchange of foreign currency. For example, a customer will have to provide the proper documentation relating to the

[7] Central bank regulations prohibit the operation of offshore trading of the Cedi.

[8] Black markets come into existence, when access to the official foreign exchange market is limited and there are various foreign exchange restrictions on international transactions of goods, services and assets. An excess demand develops for foreign currency at the official rate, which encourages some of the supply of foreign currency to be sold illegally, at a market price higher than the official rate." (see Phylaktis 1997).

[9] It should be noted that often a substantial black economy feeds the black foreign exchange market.

underlying economic transaction that is generating the demand for foreign currency. It is regulations like these that make the parallel market a suitable alternative.

Currently, there are 17 active dealer banks in the foreign exchange market. However, the top five banks account for approximately 82.3% of total volume of transactions on the FX market[10]and are thus the main market makers and play a vital role in the determination of the exchange rate. The Ghanaian FX market is a pure dealer market. Dealers usually provide liquidity to the market by absorbing order flow imbalances. This is achieved through a mixture of exchange rate adjustment and inventory management. Specifically dealers set two-way exchange rates at which customers will buy and sell FX, they absorb any excess demand or supply and then adjust exchange rates to manage their net open FX positions. Apart from providing liquidity, net open positions allow dealers to speculate against the Cedi by building positions before expected currency depreciation takes place.

Unlike many other emerging FX markets, limits are not imposed by the central bank on net open positions. Rather the central bank has opted for monitoring the foreign exchange positions, thus increasing the scope for market making. In Ghana, banks are required to report each foreign exchange transaction at their respective exchange rates. As discussed below, these are the order flow data used in this study.

In communicating and trading with each other, dealers agree to trades in telephone conversation which are later confirmed by fax or telex. There are no electronic trading platforms (like Reuters spot dealing systems) that allow for bilateral conversations and dealing. Interbank activity is relatively low.

The heavy involvement of the central bank in the FX market limits the scope for price discovery. This is because the central bank has an information advantage over the other banks due to its ability to obtain private information from the main market makers. From 2002 to present there is evidence of massive central bank intervention on the FX market. The central bank absorbs innovations in the order flow at existing exchange rates, usually with the aim of reducing exchange rate volatility.[11] The exchange rate is still determined by market forces but with the central bank absorbing part of the excess demand or supply (see Duffuor, Marsh and Phylaktis, 2009).

The high degree of concentration already mentioned above could also lead to higher transparency. Each of the dealers from the top 5 banks observe a significant proportion of the market and may have a rough idea of the trading flow that they are not

[10] See June-September 2007 Quarterly Bank of Ghana Report

[11] The central bank refers to these actions as 'balance of payment support'.

involved with. In general the central bank does not disclose information obtained from banks' reporting requirements because of the proprietary nature.

There are numerous FX bureaus that compete with the banks but they account for a small portion of the foreign exchange market. On a typical day, the daily turnover of FX bureau operators situated in the city centre ranges from $10-$20k. However, this depends on seasonal factors with peak flows being observed during the last quarter of the year, when retailers (importers) prepare for the Christmas shopping. Peak flows are also associated with Muslims' annual Hajj trip to Saudi Arabia. The USD accounts for about 2/3 of all FX transactions. Presently, the bureaus' main source of FX is the general public. The central bank ceased the supply of FX to the bureaus around 2000/2001. This move seriously affected the profitability of the bureaus because Central Bank flows represented a cheap source of funding and fierce competition developed between bureaus.

FX bureaus engage in FX transactions with banks. Their relationship can be described as a typical bank-customer relationship where bureaus operate FX deposit account with banks. Nevertheless they share a special relationship where bureaus use bank rates as a guide and banks call bureaus on a daily basis to check their rates. On average bureaus quote 'higher' rates than the banks. The difference between bank rate and bureau rates is mainly due to the relative flexibility of the bureaus. Unlike the banks, bureaus can adjust their rates about 3-4 times daily in response to market signals. Depending on the season, the parallel market (forex bureau market) is relatively more volatile. On the other hand, banks' rates rarely change during the day. Market signals include customer flows, central bank actions, actions of other bureaus etc. As and when the bureaus receive market signals, they evaluate and process this information before fixing prices accordingly.

FX bureaus are regulated by the central bank, which obliges them to submit monthly returns and financial accounts, and makes random spot checks where for example officials check whether cash tally with receipts. Nevertheless, a sizeable portion of them still engage in illegal activities. These illegal activities mainly consist of non-issuance of receipts for FX transactions and illegal remittances.[12] Ghanaian bureaus have representative/agents in London who receive remittances on their behalf. Consequently the bureaus in Ghana search for scarce FX on the market to pay the recipients. This is contrary to the normal procedure where it is rather the cedi-

[12] The central bank regulation prohibits bureaus from providing money remittances service. Yet some bureaus engage in these illegal money remittances.

equivalent of the remittance that is paid to recipients. Aside from the banks, the FX bureaus and the financial services companies for remittances constituting the forex market, there is the usual unofficial parallel forex market made up of illegal forex dealers who operate from unauthorized locations. According to the central bank, their operations constitute less than 5 percent of the forex market turnover.

Thus, certain characteristics of the microstructure of the Ghanaian foreign exchange market will have an impact on the role of order flow as a transmission mechanism for private information. The low level of interdealer market and the lack of electronic trading platforms might slow down the aggregation of private information. On the other hand, the few players in the market might increase the aggregation process because there is greater transparency as each player observes a greater proportion of the market. Furthermore, the great involvement of the Central Bank in the foreign exchange market limits the scope for price discovery. Finally, the existence of FX bureaus might contribute to the aggregation of private information as another market player closely in touch with customers.

At the same time, the Central Bank in setting the exchange rate each day could be observing the FX bureau rate as it is freely determined and changed three four times a day. Thus, there is simultaneously another dynamic relationship between the official rate and the FX bureau rate, which is linking the two rates together in the long-run and which has to be taken into account in modelling the relationship between order flow and the exchange rate.

In the next section, we present the data employed and the models we estimate.

4. DATA AND METHODOLOGY

4.1 Exchange Rate and Interest Rate Data

The Central Bank of Ghana is the main source of data for the spot foreign exchange market. The data set includes both the daily official and the FX Bureau rate, which is a proxy for the parallel (black market) cedi/dollar rates over the period 3rd January 2000 to 29th December 2007. With the exception of the parallel market, foreign exchange trading takes place during normal banking hours (9am to 4/5pm). FX bureau data is collected by the central bank daily and is the average of the individual bureau rates. It should be noted that the FX bureaus do not observe any customer order flow on the official FX market. The banks' transaction quotes represent the midrate between the bid and ask quotes at the close of each day. The transaction rate charged by a particular bank will depend on the availability of FX at that point in time.

For an emerging market like Ghana, it would be unwise to disregard the thriving black market for exchange rates. The Ghanaian Central bank acknowledges this fact and therefore incorporates black market exchange rates (FX Bureau rates) in its analysis and decision making. The official (transaction rate) is a weighted average of the rates charged of the various bank transaction rates, with the volumes used as weights, and the FX Bureau rate.

The interest rate differential is the difference between the Ghana daily three-month Treasury bill rate and the US daily three-month Treasury bill rate, expressed on an annual basis. The Ghanaian rates were collected from the Central Bank of Ghana while the US data were obtained from the Federal Reserve website.

The data sample is diverse in the sense that it contains a period of relative stability and a period of turbulence (see Figure 1a). Therefore, the sample period is divided into two sub-periods. The first sub-period represents the crisis period spanning the whole of 2000(see Figure 1b). The crisis period was characterised by spiralling inflation of more than 40% and rapid deprecation of the cedi. During 2000, the cedi depreciated by about 50% against the US dollar. This situation could be attributed to falling prices of Ghana's major exports commodities (main foreign exchange earners), namely cocoa, gold and timber. To further exacerbate this situation, the price of imported crude oil which previously hovered around $10 per barrel, soared to $34 by mid 2000. Furthermore, the official donor inflows, which hitherto had been supporting the economy, were withheld in 2000. Against all these challenges, Ghana had to pay about $200 million every month towards foreign debt obligation by drawing on the already depleting foreign exchange reserves. This created an acute shortage of foreign currency as demand for dollars far outstripped supply. In light of the fact that the nation is heavily dependent on imports, the scarcity of FX fuelled inflationary pressures. Low business confidence and political uncertainty over the outcome of the December 2000 presidential elections led to massive capital outflows around the middle of 2000. At this point, the relative scarcity of FX allowed the black market agents to demand huge premiums.[13] This contributed to the huge spike in the premium during July 2000 (see Figure 2b).

[13]The black market premium is defined as the spread between the black market rate and the official rate divided by the official rate and multiplied by 100.

The second sub period represents the relatively stable period spanning 2002-2007 (see Figure 1c).[14] By 2002 the prices of Ghana's main exports, cocoa and gold, had recovered slightly and the authorities were able to stabilise the main macroeconomic indicators. Equally important in 2002 was the resumption of intervention activity on the FX market by the central bank, which stabilised the official exchange rate.

By the end of 2001 CPI inflation stood at 21% and the Cedi depreciated by only 3.5% (see Figure 3). This was the result of tight monetary and fiscal policies. These developments contributed to the restoration of business confidence in Ghana. At the start of 2004, there is another big hike in the premium due to political uncertainty over the outcome of the December 2004 elections.

Data analysis will show that the exchange rate behaves differently during these two sub-periods.

Although the original data is at a daily frequency, preliminary regressions indicated that daily data is noisy. Consequently, we aggregate the data to a weekly frequency in an attempt to solve the problem.

We explore the long-run relationship between the official and black exchange rates, by testing whether the black market premium is stationary using the augmented Dickey-Fuller (ADF) test. The null hypothesis of a unit root is rejected in favour of the stationarity alternative for both periods.[15] This is an indication that the black market premium is stationary for both periods. In other words, the official and black rates move in tandem in the long-run.

The descriptive statistics (see Tables 1-3) indicate that the exchange rates as expected are very volatile during the crisis period, but are relatively stable during the stable period. The standard deviations are abnormally high during the crisis period, compared to that of the stable period. In order to give an idea of scale, we compare these movements to that of a larger and more liquid market like the euro-dollar. Specifically we compare the movements of the CEDI/USD to the EUR/USD over the crisis and stable period. In comparison to the CEDI/USD movements, the EUR/USD has enjoyed extreme stability. The relative stability experienced by the Ghanaian CEDI would be equivalent to a currency crisis for the Euro.

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[14] It should be noted that the transitional period between the crisis period and the relatively stable period, Jan 2001 to Jan 2002, was left out. Data during that period was noisy and could over-shadow the actual results of the analysis.

[15] Results not shown but can be provided by the authors. Similar results were found in Phylaktis and Moore (2000) for other Emerging Markets.

With the exception of black market rate changes during the crisis period, exchange rate changes are generally serially correlated. All the autocorrelations and partial autocorrelation coefficients are statistically significant (see Tables 4-7). This could be evidence of huge inefficiencies in an under-developed and illiquid market. This issue will be addressed when considering our modelling strategy.

4.2 Order Flow Data

Most banks consider their customer trades to be highly confidential and are usually reluctant to release such data to the public. In Ghana, it is a regulatory requirement for all market making banks (both Ghanaian and foreign) to report all their daily foreign exchange transactions to the central bank. These commercial banks register every single foreign exchange trade (purchase and sale) with their customers at respective transaction rates. The dataset covers the five largest banks (market-makers) in the FX market, which account for over 80% of the transactions. This leads to a high degree of transparency because an individual big bank observes a substantial portion of the market and may have an idea of order flow in the other big banks. The five banks, which form the 1st quartile of the banking industry, are in order of share of deposits Barclays Bank (BBG), Standard Chartered (SCB), Social Security Bank (SSB), Agricultural Development Bank (ADB) and Ghana Commercial Bank (GCB).[16]

The source of order flow data is the Daily Foreign Exchange Report of the Bank of Ghana (the Central Bank of Ghana), which contains all foreign exchange transactions of significant size carried out by commercial banks resident in Ghana. This data allows us to calculate daily order flow measures between domestic market-making banks and their different customer groups.

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[16] See Price Water House and Coopers (2006). SCB and BBG were the first banks to be set up in Ghana at the beginning of the 20th century. Their main line of business was trade finance and they mainly served the expatriate community. This trend has continued with a majority of their customers being multinationals and large and medium-scaled enterprises. GCB was the first indigenous bank to be set up in 1953. Its main objective was to extend credit to the local population. GCB owns about 50% of all branches in Ghana. Its customer base is well diversified with customers ranging from state enterprises to private individuals. It is the largest bank in Ghana in terms of deposits and assets. ADB was a development bank established in 1965 to cater for the needs of the agricultural sector. It has a vital role since the agricultural sector is still the largest contributor to the GDP. Until 2005 it was the sole agent for Western Union money transfer. As a result remittances account for about 90% of its foreign flows. Customer base consists of mainly small to medium scaled enterprises and private individuals. SSB is the smallest bank in the 1st quartile. It was set up by the social security and national insurance trust in 1977. Societe Generale, the French Bank, acquired controlling interest in the bank in March 2003.

This data set provides us with a relatively complete picture of the cedi/dollar market. This is similar to the datasets of Rime (2003) and Bjønnes, Rime and Solheim (2005) which account for about 90% of the Norwegian and Swedish markets respectively. The trades are aggregated over each day for each bank and for the total of the five banks. Daily order flow is calculated by taking the difference between the value of buyer initiated trades and the value of seller initiated trades. A positive order flow denotes net dollar purchases. In order to determine the sign of the trades we make the widely used assumption that trades between banks and customers are initiated from the customer side. This assumption is based on the fact that trading between banks and their customers is likely to occur when customers demand this service and therefore become initiators. Banks act as the middlemen between the interbank market and the customers. Customers place orders with their banks and then the banks trade with each other on the interbank market. The resulting order flow is what aggregates information into prices.

Unfortunately, this data set does not allow us to distinguish between the various customer groups as has been possible in some earlier studies (see Marsh and O'Rourke, 2005, Bjønnes, Rime and Solheim, 2005 and Mende and Menkhoff, 2003). Generally, the big commercial banks experience large customer order flows due to the nature of their customer base. Nevertheless, this dataset is unique in so many ways. As mentioned above it is one of few studies, which is based on a complete data set.[17] Thus, it gives a more complete picture of the FX market than studies such as Evans and Lyons (2002a), Froot and Ramadorai (2005), Marsh and O'Rourke (2005) who use data for a single market-maker and for a short period of time. Furthermore, the longer time span also allows for a more precise estimation of the impact of order flow on exchange rate movements.

4.3 Methodology

We start our analysis with the static framework proposed by Evans and Lyons (2002a) to be consistent with previous literature. Nevertheless, it is unlikely that this static model will be successful at capturing the dynamics of a largely inefficient, under-developed and illiquid FX market. Furthermore, it ignores the relationship between official and black markets. We subsequently explain the modifications to the model to

[17] It should be noted that the data covers only domestic commercial banks, as financial institutions registered outside Ghana do not have reporting obligations to the Central Bank of Ghana.

take into account the characteristics of foreign exchange markets in Emerging economies.

The generic order flow model proposed by the Evans and Lyons (2002a) can be represented by an equation of the form:

$$\Delta S_t = \alpha + \beta X_t + \gamma \Delta r_t + \varepsilon_t \tag{1}$$

where ΔS_t is the weekly change in the log exchange rate (cedi/dollar) and X_t is the total customer order flow from the top five Ghanaian commercial banks. Δr_t represents the change in the nominal interest rate differential, $\Delta(i_t - i_t^*)$ where i_t is the weekly nominal Ghanaian three-month treasury bill (t-bill) rate and i_t^* is the weekly nominal US three-month t-bill rate. Customer Order flow is measured in millions of US dollars. When β, the coefficient of order flow, is positive and significant we say that the purchase of dollars by customers results in a depreciation of the cedi (an increase in the exchange rate versus the dollar). This refers to the null hypothesis of the order flow concept. The null hypothesis states that information from order flow causes exchange rate changes.

We modify the generic model in the following ways. First, as indicated by the presence of autocorrelation in exchange rates, there are inefficiencies in the Ghanaian foreign exchange markets (see Tables 4-7). We capture the dynamics in the market by including lags of both the explanatory and dependent variables. We are thus taking into account the fact that changes in order flow and interest rate differential may not affect the exchange rate immediately but rather with a lag over several time periods. When customer trades are executed, there may be some delay in the time it takes for the information conveyed by trades to be embedded in exchange rate. As explained in section 3, features of the Ghanaian foreign exchange market might affect the aggregation of information and the impact of order flow on exchange rates.

Second, we include the black market premium to take into account the long-run relationship between the black and official exchange rates.

Third, we explore whether the explanatory power of order flow comes from its expected, unexpected component or both. In the Evans and Lyons (2002a) model, all order flow is deemed to be unexpected (and statistically this assumption appears to be borne out by the unpredictability of most major market order flow series at daily horizons). However, in the case of Ghana we will demonstrate that order flow is to some extent predictable and it is possible that explanatory power comes from both the expected and unexpected components. In this case, whilst unexpected order flow measures price discovery in the FX market, expected flow would be an indication of inefficiencies in the FX market.

Our modified model is based on an enriched version of the VAR in Love and Payne(2008). We say 'enriched' in the sense that, though we drop the news variable from their equation, we include lagged changes in the black and official market rates, lagged changes in the interest differential and lagged black market premium. We decompose order flow into expected (EF) and unexpected (UF) components and determine which component accounts for movements in the official and black exchange rates.

The equation for the official exchange rate is given below:

$$\Delta S_t = \alpha_1 + \sum_{i=0}^{4}\beta_i EF_{t-i} + \sum_{i=0}^{4}\tau_i UF_{t-i} + \sum_{i=1}^{4}\sigma_i \Delta r_{t-i} + \sum_{i=1}^{4}\delta_i \Delta B_{t-i} + \sum_{i=1}^{4}\gamma_i \Delta S_{t-i} + \kappa P_{t-1} + \mu_t \qquad (2)$$

where ΔS_t is the log change in official exchange rate, X_t is the net order flow, ΔB_t is the log change in the black market rate, Δr_t is the change in the interest differential and P_t is the black market premium. We estimate equations for the exchange rate and the order flow individually using OLS.

The decomposition of the contemporaneous order flow X_t into its expected and unexpected components is done using a two stage procedure. Order flow is first regressed on changes in the interest rate differential, the lagged black market premium, lagged values of order flow and lagged exchange rate changes (both official and black market).

$$X_t = \alpha_2 + \sum_{i-1}^{4}\beta_i X_{t-i} + \sum_{i=1}^{4}\gamma_i \Delta S_{t-i} + \sum_{i=1}^{4}\delta_i \Delta B_{t-i} + \sum_{i=1}^{4}\sigma_i \Delta r_{t-i} + \kappa P_{t-i} + \mu_t \qquad (3)$$

We store the fitted values as expected flows and the residuals as unexpected flows. We then substitute the expected and unexpected flow variables in the exchange rate equation and run the regression. This is done for both the official and black market exchange rates. Specifically one equation has changes in the official exchange rate as the dependent variable, whilst the other has changes in the black market rate as the dependent variable.

Since these equations have many regressors we adopt the general to specific modelling approach. Specifically we start with an extremely general model, which is over-parameterised, then we reduce it to the most parsimonious model by testing various coefficient restrictions. We start with a maximum lag length of 4. Schwarz's (1978) Bayesian information criterion (SBIC) is used to determine the appropriate lag length for the variables in this dynamic equation. We choose the lag length which minimises the SBIC. We also apply the Newey-West procedure which results in standard errors that are consistent in the presence of both heteroscedasticity and serial correlation. It should be noted that we estimate the regressions for the two sub-periods separately.

5. Empirical Evidence

5.1 Main Results

Table 8 reports the estimates of the static model. The dependent variable is the weekly log change in cedi/dollar exchange rate. The regressor X_t is the weekly net customer order flow. The regressor (Δr) represents the change in the interest rate differential. Customer order flows are significant in this generic static model. In other words, customer order flows are able to explain contemporaneous movements in the exchange rate. Nevertheless, order flow variables are negatively signed, contrary to what is expected. Thus, over the whole period, customer trades may not convey any incremental information relevant to exchange rates. These negative results could emanate from the heterogeneity of our data sample and/or the static nature of our model. As already discussed we tackle sample heterogeneity by dividing the sample into sub-periods. The first sub-period represents the crisis period spanning January 2000 to December 2000 when the exchange rate depreciated by almost 50%. The second sub-period corresponds to the relatively stable period spanning March 2002 (when central bank resumed intervention) to December 2007. We believe that these different sub-periods may/will have an effect on the relationship between order flow and exchange rates.

For the crisis period, the order flow variable is positively signed and significant in explaining movements in the official exchange rate (see Table 8). This means that a net purchase of dollars by customers is associated with a depreciation of the cedi. The interest differential is also positively signed and significant as expected. When the dependent variable is the change in the black market rate, order flow is not significant. In other words, flows have no explanatory power in the black market during the crisis period. The interest differential is however highly significant and correctly signed in both markets.

During the stable period, order flow is highly significant but negatively signed with the official exchange rate as the dependent variable. For the black market rate order flow is only significant at 10% significance level but is still negatively signed. The interest differential is insignificant.

In general, the results of the static model are unconvincing. Given the peculiarities of the Ghanaian FX market we proceed to estimate the modified model as represented by equations (2) and (3). Detailed results for the order flow are presented in Table 9, while for the exchange rate are presented in Table 10. Looking first at the results for order flow we observe positive momentum during the stable period and negative momentum during the crisis period.[18] The interest rate differential is only statistically significant during the crisis period. The adjusted R^2 during the stable (crisis) period is 0.376(0.290). The estimated values of the equation form the expected component of order flow and the residuals the unexpected.[19]

In general both expected and unexpected components (current and/or lagged) of order flow are significant in explaining movements in exchange rates. Specifically, during the crisis period expected and unexpected flows have an instantaneous and lagged effect on the official exchange rate. However, they both have only lagged effects on the black market exchange rate. Another important observation is that the lagged black market premium is statistically significant in the black market exchange rate. It is negative. This negative correlation implies that an increase in the (black market) premium is associated with an appreciation of the black market rate. Thus, in the long-run, the black market rate eventually adjusts to the official rate. The interest rate differential is positive as expected and statistically significant only in the official market indicating that different factors might affect the black market rate. The adjusted R^2 varies from 0.240 to 0.697 and is higher in the official market.

A clearer picture emerges about the impact of order flow on the exchange rate when we add up the coefficients of the lags of the order flow components in the specific model (see Table 11). For example, an unexpected net customer purchase of \$1bn over the previous four weeks during the crisis period will result in 37% depreciation of today's exchange rate.

In the official market, unexpected order flow has a larger impact on exchange rates relative to expected order flow and is correctly (positively) signed for both crisis and stable periods. Results for the black market are mixed. Unexpected order flow has a relatively smaller impact for both periods but is negatively signed during the stable

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[18] One would have expected the otherway round as the black market rate is more flexible than the official rate. It might be that in the case of Ghana the reforms of the FX market have eroded the importance of the black market to such an extent that it can be disregarded for most of the major results in this paper.
[19] In addition to the decomposition used in the paper, we also decompose flows based on fundamentals. Our results carry through.

period. We also observe that the coefficients during the crisis are generally much larger in magnitude compared to those in the stable period. In other words the dollar impact of flows on exchange rates is much larger in the crisis period. This is consistent with findings by Marsh and O'Rourke (2005). They find that there is a connection between the magnitude of coefficients and the liquidity of the FX market. Specifically in very liquid markets (like the euro-dollar and dollar yen) coefficients are relatively small in comparison to the larger coefficients in the smaller, less liquid markets (like the euro-yen and pound-yen). Similarly in our case the magnitude of the coefficients are much larger during the crisis period when the cedi-dollar market is almost illiquid compared to the coefficients in the stable period when the market is relatively liquid. In other words, the magnitude of the impact of order flows on exchange rates depends on the level of liquidity in the Ghanaian FX market.[20]

In most cases other variables like the lagged changes in exchanges rates (official and black) are very significant. As discussed previously this is consistent with the inefficiencies and under-development in the Ghanaian FX market. As a result agents' speculation about future exchange rate movements is based on immediate past values of the exchange rate itself. Subsequently an initial depreciation induces a series of buying which causes a further depreciation of the domestic currency.

5.2 Temporary or Permanent effects of order Flow?

It is critical to order flow literature to ascertain whether impacts are temporary or permanent. If the effects of unexpected flows are permanent then that means information is being conveyed by flows. On the other hand, the temporary effect of unexpected flows could be as a result of a variety of liquidity effects. To find out whether effects of flows are temporary or permanent, we test for the significance of aggregated effect. We conduct a Wald coefficient restriction test on the flow variables. This consists of an F-test with a null hypothesis that the sum of the coefficients is zero. In other words the null hypothesis states that the aggregate effect of flows is temporary. A rejection of the null in favour of the alternative could mean that the aggregate effects of flows are permanent and vice versa. The Wald tests were conducted on the specific models, i.e. when the insignificant coefficients have been eliminated.

Unexpected order flow has a permanent effect for both periods only in the official market. This could be interpreted to mean that unexpected order flow conveys incremental information which causes changes in the exchange rate (see Table 12).

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[20] Supporting evidence of the reduced liquidity during the crisis period is provided by the much higher bid/ask spread for both the official and black markets. The spread in the official (black) market was 0.250 (0.418) during the crisis period, compared to 0.120 (0.237) during the stable period.

5.3 Interpretation of Results

During the crisis period, unexpected order flow has a larger permanent effect on official and is positively (correctly) signed. Though unexpected order flow is positively signed in the black market, its aggregate effect is only temporary. According to literature this is what we should expect. During this turbulent period, falling cocoa and gold prices coupled with rising oil prices and donor inflows being withheld led to expectations of poor future fundamentals. This induced an excess demand for FX and economic agents, who were in a state of panic and were willing to pay high premiums for an already scarce commodity. This continuous bidding-up of FX at high premiums led to a spiralling of the exchange rate and contributed to the 50% depreciation.

During the stable period both expected and unexpected flows have a permanent impact on the official exchange rate. Again, unexpected order flow has a relatively larger impact and is positively signed. Nevertheless, the price-impact of unexpected order flow is much lower during the stable period. As previously discussed, this could be related to the level of liquidity during both periods. Interestingly, even though expected order flow has a smaller impact, its effect is permanent and is negatively signed. During this calm period, a significant portion of the FX transactions are carried out by corporates (mostly multinationals) who are often assumed to follow negative feedback trading rules. In other words, corporates buy the currency that has just depreciated. According to existing literature corporates usually take advantage of these short-term exchange rate movements to exchange money for non-speculative reasons like repatriation of funds and import of raw materials. The presence of negative feedback trading is confirmed by the highly significant and negatively signed lagged exchange rate variables in the order flow VAR (see Table 10). Thus negative feedback trading of corporates is over-shadowed by the price discovery/information aggregation process.

On the black market, Expected and unexpected order flow have only temporary effects and are both negatively signed. The absence of price discovery reflects the nature of transactions on the black market. The official FX market is relatively stable and it costs less (and is more convenient) for customers (individuals and institutions) to obtain FX from the banks. As a result a majority of the flows are seen by commercial banks. By observing the coefficients we see that the price-impact is relatively small in comparison to the other flows. This is because there are many small players on the black market who observe significantly smaller flows in comparison to the banks.

These results further confirm previous findings that it is rather the black market rate that adjusts to the official spot rate.

5.4 Modelling the long-run relationship between exchange rate and order flows

Previous tests we conducted have been aimed at capturing the short-term dynamics in the Ghanaian FX market. Next, we attempt to investigate the long-run relationship between the levels of exchange rate and the cumulative customer order flow. Since the black market rate is rather adjusting to the official rate, we include only the level of the official rate and cumulated order flow in our cointegration analysis.

Using the augmented Dickey-Fuller (ADF) test (Table 13), we confirm that the two series are non-stationary. Thus, the null hypothesis is the level of official exchange rate and cumulative customer order flow are not cointegrated, against an alternative of one cointegrating vector. We determine the lag length of 4 for the VAR using Schwarz Bayesian Information Criterion (SBIC). According to the Johansen procedure, the null of no cointegration is rejected at 5 percent level and further suggests that there is only one cointegrating vector (Table 14). We estimate the vector error-correction model. The coefficients of the cointegrating relationship are significant and correctly signed (Table 15). Results from the short-run dynamics are reinforced as the cumulative customer order flow is positively correlated with the levels of official exchange rate. In order to have an idea of which variables provide adjustment to equilibrium, we examine the error correction coefficients, which are highly significant in both the order flow and exchange rate equations (Table 15). This means that tests for weak exogeneity have been strongly rejected for both variables. The load of adjustment towards long- run equilibrium falls solely the official exchange rate. The negative (wrong) sign of the error correction in the flows equation indicates that flows do not adjust to cause equilibrium but rather move in the opposite direction. However the relatively higher speed of adjustment of flows means that eventually flows should 'catch up' with the official exchange rate in order for the whole system to attain the equilibrium. Clearly these cointegration results could be described as weak because the adjustment process is ambiguous.

6. Discussion and Conclusion

In Ghana, customer order flow greatly influences exchange rates, reinforcing the importance of order flow stated in previous literature. In considering an emerging market like Ghana, we need to consider some distinct features of the economy. The economic fundamentals governing the Ghanaian cedi are mainly dependent on external factors, mainly world commodity prices and foreign capital flows. For several years the Ghanaian cedi has remained vulnerable. Therefore, it could be argued that the trades of customers of the top foreign banks, who control about 80% of the FX market, may convey more superior private information about future fundamentals than their local counterparts. At the same time however, we can not ignore the existence of the black market for foreign exchange.

We test our data using the Evans and Lyons (2002a) model and find that it does not work. We modify itto take into account the market inefficiencies, poor infrastructure and lack of advanced technology in the Ghanaian FX markets which create delays in the price transmission mechanism. We attempt to capture these delays and other inefficiencies by introducing a dynamic model. Additionally, we take into account the long-run relationship between the black and official rates. Furthermore, we investigate whether the expected or unexpected component of order flow is responsible for movements in the exchange rates. Evidence of a permanent effect of unexpected flows would mean that they convey private information and as a result there is price discovery. Significant impact of expected order flow on the exchange rate would represent inefficiencies in the FX market.

Our results indicate that unexpected order flow has a permanent effect only in the official market during both periods. This is consistent with previous literature that unexpected flows convey incremental private information that affects exchange rates. In other words, it is the shock component of flow that matters. We find that unexpected order flow is highly significant and positively correlated with changes in the official. The only exception is the black market during the stable period where unexpected order flow is negatively correlated with exchange rates. In the official market, unexpected order flow has a relatively larger impact on the exchange rate changes than expected order flow for both crisis and stable period. The smaller impact of unexpected order flow on the black rate might be due to the fact that there are numerous smaller players in the black market. The lack of price discovery in the black market could be due to the fact that a majority of the FX transactions (by corporates and individuals) occur in the official market. On the other hand transactions on the black market are significantly lower in terms of volume and value. Not surprisingly most of these transactions are conducted by individuals and petty traders. During the 3rd quarter of 2007, total purchases by banks was \$1.1bn compared to \$96m for forex bureaus whilst total sales by banks was \$882m compared to \$95m for forex bureaus. We also observe that the lagged black market premium (which is highly significant) is negatively correlated with changes in the black market rate. This suggests that it is rather the black market rate that adjusts to the official rate to cause a return to equilibrium.

Cointegration tests reveal that there is a long-run relationship between levels of official rates and cumulative order flow. Consistent with market microstructure theory, cumulative order flow is positively correlated with the official exchange rate. Furthermore the official rate is largely responsible for the adjustment to equilibrium.

Our results give us a deeper insight into the relationship between order flow and the exchange rates for different regimes in emerging markets. Specifically, there is strong evidence of information aggregation and price discovery for the official market during both regimes, similar to findings of Evans and Lyons (2002a). However for the official FX market during the stable period, order flow is as a result of negative feedback trading by corporates similar to findings by Marsh and O'Rourke (2005). Unexpected order flow is correctly signed and has a larger impact on exchange rate as theory suggests. Nonetheless, expected order flow too seems to have an impact on order flow and this is due to inefficiencies in the FX market. There is evidence of both price discovery and negative feedback trading but the former overshadows the latter.

Not only do we confirm the contemporaneous relationship (between flows and exchange rate) suggested by previous literature (Evans and Lyons (2002a) but we also observe a lagged interaction between order flow and exchange rates. These lagged effects are due to the delays in the price transmission which are associated with inefficiencies in the FX market. Additionally we observe that when the market is almost illiquid during crisis, order flow has a relatively larger impact on exchange rates than in the stable period when the market is more liquid. This confirms findings by Marsh and O'Rourke (2005) who find that there is a connection between the price impact of the order flow and the degree liquidity in the FX market.

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Table 1: Descriptive statistics for changes in exchange rates for whole period

	Changes in spot	Changes in black
Mean	0.2428	0.2474
Median	0.0638	0.0631
Maximum	4.3725	6.2064
Minimum	-0.8962	-1.7375
Std. Dev.	0.6225	0.7977
Observations	412	412

Descriptive statistics for weekly changes in log of exchange rates calculated over the period January 2000 to December 2007

Table 2: Descriptive statistics for changes in exchange rates for crisis period

	Changes in spot	Changes in black	Euro-dollar
Mean	1.3130	1.2634	-0.000319
Median	1.0953	0.6221	-0.000492
Maximum	4.3725	6.2064	0.042041
Minimum	-0.8847	-1.7375	-0.02252
Std. Dev.	1.2429	1.7591	0.008665
Observations	51	51	51

Descriptive statistics for weekly changes in log of exchange rates calculated over the period January 2000 to December 2000

Table 3: Descriptive statistics for changes in exchange rates for stable period

	Changes in spot	Changes in black	Euro-dollar
Mean	0.0850	0.0851	0.000253
Median	0.0407	0.0641	0.000322
Maximum	0.9732	1.6969	0.02521
Minimum	-0.7421	-1.3977	-0.021333
Std. Dev.	0.1894	0.3303	0.005724
Observations	300	300	300

Descriptive statistics for weekly changes in log of exchange rates calculated over the period march 2002 to December 2007

Table 4: Autocorrelation Function for changes in official exchange rate for crisis period

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
**|. |	**|. |	1	-0.299	-0.299	21.558	0.000
**|. |	***|. |	2	-0.224	-0.344	33.658	0.000
.|** |	.|. |	3	0.238	0.057	47.455	0.000
*|. |	*|. |	4	-0.128	-0.114	51.429	0.000
.|. |	.|. |	5	-0.031	-0.031	51.66	0.000
.|* |	.|. |	6	0.074	-0.027	52.993	0.000
*|. |	*|. |	7	-0.119	-0.11	56.48	0.000
.|* |	.|. |	8	0.098	0.041	58.843	0.000
.|* |	.|* |	9	0.116	0.129	62.204	0.000
*|. |	.|. |	10	-0.177	-0.038	70.088	0.000

Table 5: Autocorrelation Function for changes in black exchange rate for crisis period

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.035	-0.035	0.2888	0.591
.|. |	.|. |	2	-0.054	-0.055	0.9865	0.611
.|. |	*|. |	3	-0.057	-0.061	1.7661	0.622
.|* |	.|* |	4	0.103	0.097	4.3785	0.357
.|* |	.|* |	5	0.117	0.12	7.7131	0.173
.|. |	.|. |	6	-0.017	0	7.7827	0.254
.|. |	.|. |	7	-0.016	0.006	7.8462	0.346
.|. |	*|. |	8	-0.057	-0.058	8.6492	0.373
.|. |	.|. |	9	0.043	0.013	9.1168	0.427
.|* |	.|* |	10	0.131	0.119	13.389	0.203

Table 6: Autocorrelation Function for changes in official exchange rate for stable period

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| |	***| |	1	-0.448	-0.448	295.17	0.000
| |	**| |	2	0.008	-0.241	295.26	0.000
| |	*| |	3	0.049	-0.072	298.86	0.000
*| |	*| |	4	-0.063	-0.087	304.71	0.000
|* |	|* |	5	0.129	0.093	329.08	0.000
*| |	| |	6	-0.085	0.022	339.8	0.000
|* |	|* |	7	0.098	0.124	353.91	0.000
| |	|* |	8	-0.023	0.091	354.66	0.000
| |	| |	9	-0.008	0.064	354.74	0.000
|* |	|* |	10	0.082	0.119	364.67	0.000

Table 7: Autocorrelation Function for changes in black exchange rate for stable period

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.105	0.105	16.224	0.000
|* |	|* |	2	0.164	0.155	55.883	0.000
|* |	|* |	3	0.094	0.066	68.938	0.000
|* |	| |	4	0.08	0.043	78.343	0.000
|* |	| |	5	0.067	0.034	84.915	0.000
| |	| |	6	0.04	0.008	87.247	0.000
| |	| |	7	0.001	-0.027	87.25	0.000
| |	| |	8	0.033	0.019	88.889	0.000
| |	| |	9	-0.012	-0.021	89.086	0.000
| |	| |	10	-0.01	-0.018	89.241	0.000

Table 8: generic model 1: Regressing weekly change in log exchange rates (both official and black market) on total order flow and change in interest differential over the whole sample period and the two sub-periods: $\Delta S_t = \alpha + \beta X_t + \gamma \Delta r_t + \varepsilon_t$

	Whole sample period Jan 2000 – Dec 2007		Crisis Period Jan 2000 – Dec 2000		Stable Period Jan 2002 – Dec2007	
	Official Exchange rate	Black Market Exchange rate	Official Exchange rate	Black Market Exchange rate	Official Exchange rate	Black Market Exchange rate
Total Order flow, X_t	-1.548 (-3.085)	-1.727 (-3.354)	1.259 (2.456)	0.494 0.741	-3.965 (-2.364)	-3.471 (-1.506)
Change in interest diff. , Δr	0.249 (1.576)	0.308 (1.244)	0.538 (4.325)	0.900 (3.000)	-0.004 (-2.364)	0.001 (0.013)
Adjusted R^2	0.076	0.061	0.146	0.138	0.003	-0.001
P-value serial correlation LM test	0.000	0.000	0.010	0.149	0.062	0.000
P-value, white heteroscedasticity test	0.001	0.000	0.902	0.789	0.298	0.162

T-values are in parentheses. Standard error estimates are corrected for serial correlation and heteroscedasticity using the Newey-West HAC correction. All equations are estimated using basic OLS. We scale the order flow coefficients by multiplying by 10.

Table 9: Order Flow VAR for crisis and stable periods. Order flow is regressed on its own lags, lagged exchange rate changes, lagged black exchange rate changes and lagged interest differential

$$X_t = \alpha_2 + \sum_{i-1}^{4} \beta_i X_{t-i} + \sum_{i=1}^{4} \gamma_i \Delta S_{t-i} + \sum_{i=1}^{4} \delta_i \Delta B_{t-i} + \sum_{i=1}^{4} \sigma_i \Delta r_{t-i} + \kappa P_{t-i} + \mu_t$$

	Crisis Period	**Stable Period**
X_{t-1}	-3.885 (-3.180)	1.361 (2.243)
X_{t-2}	-2.801 (-3.233)	1.824 (2.878)
X_{t-3}		1.521 (2.605)
X_{t-4}		1.706 (2.627)
ΔS_{t-1}	-0.593 (-02.011)	-0.501 (-1.942)
ΔS_{t-2}		-0.396 (-2.086)
ΔB_{t-2}	0.681 (2.207)	
ΔB_{t-3}	-0.159 (2.262)	
Δr_{t-1}	-0.860 (-3.451)	
Δr_{t-4}	-0.477 (-3.478)	
Adjusted R^2	0.376	0.2903
P-value, serial correlation LM test	0.861	0.102
P-value, white heteroscedasticity test	0.024	0.074

Table 10: Expected and unexpected order flows for crisis and stable periods. Changes in the official exchange and black market rates are regressed on its own lags, current and lagged expected and unexpected order flows, lagged black exchange rate changes, lagged interest differential

$$\Delta S_t = \alpha_1 + \sum_{i=0}^{4}\beta_i EF_{t-i} + \sum_{i=0}^{4}\tau_i UF_{t-i} + \sum_{i=1}^{4}\sigma_i \Delta r_{t-i} + \sum_{i=1}^{4}\delta_i \Delta B_{t-i} + \sum_{i=1}^{4}\gamma_i \Delta S_{t-i} + \kappa P_{t-1} + \mu_t$$

	Crisis Period		Stable Period	
	Official Exchange Rate	Black Market Exchange Rate	Official Exchange Rate	Black Market Exchange Rate
EF_t	2.854 (4.121)		-10.650 (-9.289)	
EF_{t-1}			5.134 (5.985)	
EF_{t-2}		1.793 (2.149)	4.914 (5.418)	1.828 (1.700)
EF_{t-3}	-1.748 (-3.641)	2.537 (1.849)	-1.411 (-2.874)	-2.513 -2.361
UF_t	2.367 (4.059)			
UF_{t-1}			1.480 (7.158)	0.453 (2.006)
UF_{t-2}	1.379 (1.836)	1.779 (1.958)	1.458 (7.938)	
UF_{t-3}			0.358 (2.264)	-0.591 -2.119
ΔS_{t-1}	0.202 (2.693)	0.331 (2.535)	-0.369 (-4.755)	
ΔS_{t-2}	0.363 (3.252)		0.397 (9.188)	
ΔS_{t-3}			0.266 (4.201)	
ΔB_{t-1}		0.426 3.305		0.471 (6.142)
ΔB_{t-2}	-0.201 (-2.587)		-0.048 (2.924)	-0.099 (-1.709)
ΔB_{t-3}	0.354 (4.319)			
Δr_{t-1}	0.838 (4.424)			
Δr_{t-2}			0.036 (3.034)	
Δr_{t-3}	-0.469 (-4.001)		-0.033 (-3.121)	
ΔP_{t-1}		-0.300 (-3.282)		-0.059 (-3.119)
Adjusted R^2	0.542	0.303	0.697	0.240
P-value, serial correlation LM test	0.277	0.979	0.000	0.386
P-value, white heteroscedasticity test	0.997	0.059	0.000	0.029

T-values are in parentheses. Standard error estimates are corrected for serial correlation and heteroscedasticity using the Newey-West HAC correction. All equations are estimated using basic OLS. We scale the order flow coefficients by multiplying by 10.

Table 11: Aggregate impact of Order Flows

		Crisis Period		Stable Period	
		Official	Black	Official	Black
Specific	UF	**0.3748**	0.1780	**0.0330**	-0.0014
	EF	**0.1105**	0.4330	**-0.0202**	-0.0070

In order to calculate the overall impact, we just add up the coefficients of the lags. UF (EF) stands for unexpected (expected) flows.

Table 12:P-values from Wald coefficient restriction test for specific and models

		CRISIS PERIOD		STABLE PERIOD	
		Official	Black	Official	Black
Specific	UF	**0.3748 [0.0001]**	0.1780 [0.0574]	**0.03300 [0.0000]**	-0.0014 [0.6620]
	EF	0.1105 [0.0728]	0.4330 [0.0491]	**-0.02020 [0.0000]**	-0.0070 [0.0953]

P-values are in brackets UF (EF) stands for unexpected (expected) flows.

Table 13 : Unit Root test on level of Official rate and cumulative order flow

Unit root test	Levels of official rate	Cumulative order flow
P-value	**0.7222**	**1.0000**
t-statistic	**-1.0851**	**4.4398**

Table 14: Cointegration relationship between exchange rates and cumulative order flows

	Max. Eigenvalue statistic	**Trace test statistic**
	46.75775	**54.47287**
	(15.89210)*	**(20.26184)***

* 5% critical value of unrestricted cointegration rank test. Both denote significance

Table 15: Cointegration equation

Cointegrating Equation

P_{t-1}	**1.0000**
X_{t-1}	**-0.000799** **[-5.72540]**

t-statistics in []

Table 16: Vector Error Correction Estimates

D variable	ΔP_t	ΔX_t
ECM coef	-0.00083 [-4.43738]	-5.30524 [-6.94557]
ΔP_{t-1}	-2.31826 [-3.97148]	-758.634 [-3.18338]
ΔP_{t-2}	0.04154 [0.69206]	-790.349 [-3.22494]
ΔP_{t-3}	0.38378 [6.41109]	-444.026 [-1.81686]
ΔX_{t-1}	-0.00002 [-0.96660]	0.05930 [0.94762]
ΔX_{t-2}	-0.00003 [-2.04078]	0.10828 [1.74075]
ΔX_{t-3}	-0.00003 [-2.03215]	0.07526 [1.20896]
Adj R^2	0.219622	0.273320

Figure 1a: weekly spot Exchange rates for the whole sample period

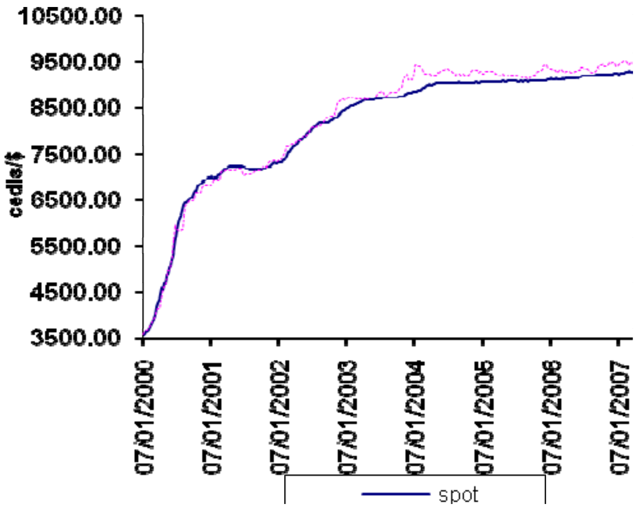


Figure 1b weekly spot Exchange rates during crisis period

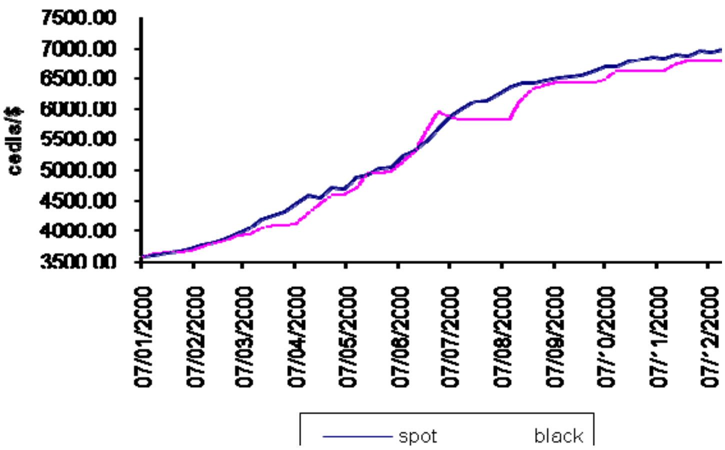


Figure1c weekly spot Exchange rates during

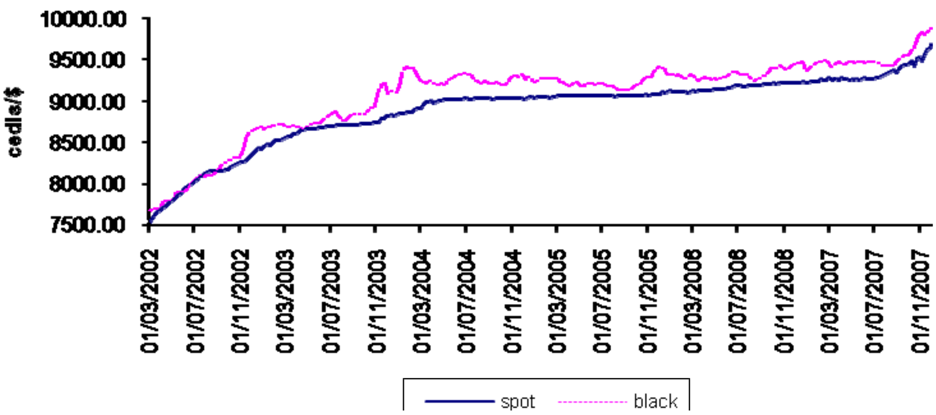
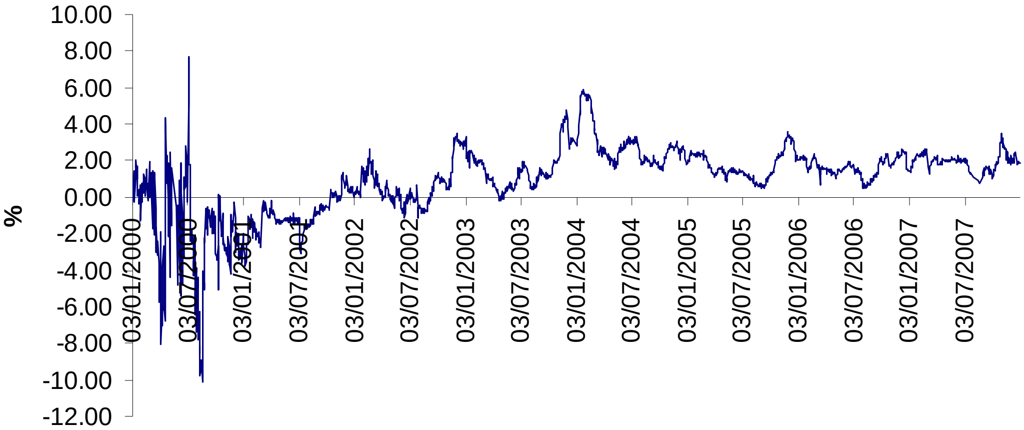
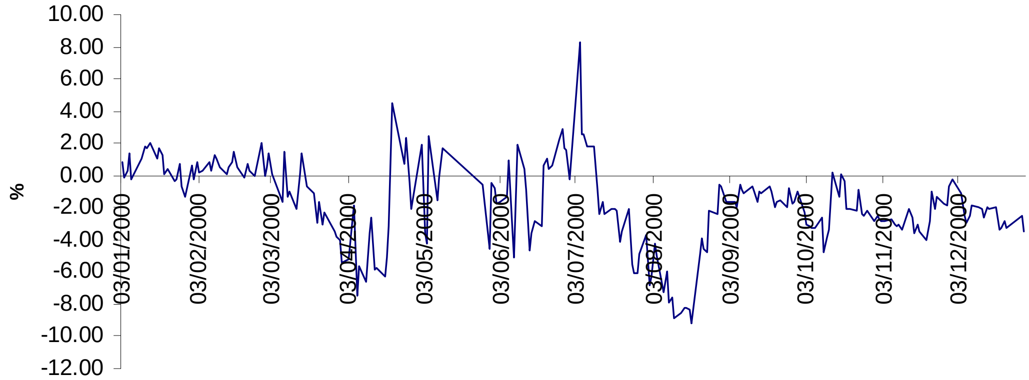


Figure 2a: Black market premium

black market premium over whole period



black market premium over crisis period



black market premium over stable period