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Liquidity, Volatility and Intervention: An Analysis of the Jamaican Foreign Exchange Market

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Abstract

This paper analyses daily liquidity and volatility in Jamaica's foreign exchange market with the objective of employing these measures as signals to assist in informing monetary policy. Given the thinness of the market, several measures of liquidity were derived to assess the level of liquidity in the JMD/USD market. It was determined that order flows, which closely match net demand for US dollars is the most suitable measure of liquidity. Maximizing the likelihood function of an ordered probit model for central bank intervention suggested different threshold levels for the depreciation and the appreciation of the Jamaica Dollar. The results suggest that signals for intervention are not symmetric and various analytical tools should be employed in informing the timing of intervention.

Key words: *Liquidity, volatility, intervention, GARCH, ordered probit, market microstructure, policy.*

JEL Classification: *G00, G19, G12,*

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1.0 Introduction

The use of market microstructure models has become very popular in financial market research stemming from the inability of traditional macroeconomic models to adequately capture the short-term dynamics of financial markets (Frankel and Froot, 1990). Studies in the market microstructure field have focused primarily on asset markets in an attempt to model the behavior of market makers in price determination. These market makers are seen as intermediaries who fill the gaps that arise from the imperfect synchronization between the arrivals of buyers and sellers (Grossman and Miller, 1988). In regard to the foreign exchange market, market microstructure models are used to analyze the information inherent in market order flows and the impact of these flows on exchange rate movements[1].

In addition, a number of studies on the microstructure of foreign exchange markets have looked at the relationships between trading volume, volatility and bid-ask spreads from both a theoretical and an empirical point of view. From a policy perspective, understanding these relationships are important because of their implications for the analysis of the nexus between market liquidity and market risk. Broadly speaking, a market is considered to be liquid when large transactions are executed with a small impact on prices (BIS, 1999). In practice, however, no data are available that allow this definition of foreign exchange market liquidity to be measured directly. Instead, trading volumes or bid-ask spreads are frequently used as indirect measures. Volatility is often considered as a measure of risk.

This paper examines the relationship between liquidity and volatility in the foreign exchange market and the effect of any market response from the Bank of Jamaica (BOJ) on exchange rate changes, using a market microstructure approach. Over the past decade, there has been a sustained depreciation in the value of the Jamaica Dollar vis-à-vis the US dollar (JMD/USD), with several bouts of large and protracted volatility in the exchange rate. This phenomenon has prompted episodes of central bank intervention

[1] Order flow is determined by the difference between seller initiated trade volumes and buyer initiated trade volumes.

aimed at stabilizing foreign exchange market activity. From a historical perspective, the BOJ tends to intervene in the foreign exchange market whenever market activity appears disorderly. Monitoring exchange rate misalignments is one of the analytical tools employed by the BOJ to inform monetary policy. This monitoring exercise is important in the sense that an overvaluation of the real exchange rate can undermine export competitiveness and weaken Jamaica's external liquidity position, while an undervaluation may create inflationary pressure. Disorderly markets involve a collapse of liquidity, where market intermediaries face difficulties matching suppliers with end users of foreign currency. If market illiquidity persists, it can have serious adverse effects on the real economy and, as such, it is usually not ignored by the Bank. Tolerating occasional episodes of illiquidity, however, is necessary to allow the market to self-correct and to expose market participants to risks inherent in trading financial assets.

A number of indicators can be used to detect and measure market illiquidity including: (i) exchange rate changes; (ii) exchange rate volatility; (iii) exchange rate bid-ask spreads; and (iv) the level and composition of foreign exchange market turnover. In this paper, a few of these indicators are employed as signals for intervention. In particular, as a primary contribution of this paper, a threshold level for exchange rate volatility, based on the level of liquidity in the market is determined. This is aimed at providing policy makers with an additional set of empirical and analytical tools to carry out more timely interventions.

This paper analyses key aspects of market microstructure to the foreign exchange market in Jamaica over the period January 2001 to June 2010. First, this paper analyses the liquidity in the foreign exchange market and looks at the implications for monetary policy. Following Mancini *et al.* (2010), several measures of liquidity are derived to assess the level of liquidity in the JMD/USD market. Second, a GARCH model, used to determine volatility and order flows, used as a measure of liquidity, are used to examine their effects on exchange rate changes in a model similar to that of Evans and Lyons (2001). Finally, an ordered probit model is used to determine the factors that influence BOJ's intervention in the JMD/USD market. This is supported by maximizing a likelihood function of the ordered probit model to derive threshold values of a reaction function for intervention to signal to the BOJ an appropriate time to enter the market.

The remainder of the paper is organized as follows. Section 2 provides a review of the relevant literature. In section 3 the various measures of liquidity and volatility for the Jamaican foreign exchange market are estimated. Section 4 presents a model of the price impact of trade, while section 5 outlines the ordered probit model. In section 6 the results of the models are presented and section 7 highlights the policy implications. A summary of the findings is presented in the final section.

2.0 Literature Review

Exchange rate models to a large extent have focused on the behaviour of macroeconomic variables in exchange rate determination. More recently, these models have been criticized for their inability to capture the short-run dynamics that exist in the foreign exchange markets (Frankel and Froot, 1990). It is argued that the fundamentals involved in the macroeconomic analysis of the foreign exchange market pay "little attention to how the trading in the foreign exchange market actually takes place" (Evans, 2005, p. 1). These trade details have been found to have a significant impact on the market, particularly with regards to the importance of information in price determination. Evans (2005) outlines a microstructure model for the foreign exchange market as being one in which dealers and customers are heterogeneous, information about the current and future state of the economy is widely dispersed, order flows provide relevant information to the market as it relates to the demand and supply of currency and inter-dealer trades allow private information from customers to be disseminated across the market.

Given this theoretical construct, several studies on the microstructure of the foreign exchange market have been conducted to analyze the level of liquidity (Macini *et al.*, 2010), order flows (Evans and Lyons, 2002 and Khemraj *et al.*, 2009), volatility (Hseih, 1988 and Baille and Bollerslev, 1989) and intervention (Hassan, 2009). Liquidity in the foreign exchange market is of utmost importance as it is reduces the net buying or selling pressure on exchange rates. The more liquid a currency is, the less likely will there be fluctuations in the exchange rate, implying greater stability in the market. Macini *et al*. (2010) developed various liquidity measures for the foreign exchange market, quantified the commonality in liquidity across different exchange rates and determined the liquidity risk premia in foreign exchange returns. They used intraday data for nine currency pairs over the period 3 January 2007 to 22 December 2008. Liquidity was measured using intra-day return reversal which captured the cross-sectional and temporal variation in liquidity. They also decomposed exchange rate liquidity into the idiosyncratic and common components, where the latter was modeled to determine the market-wide effects on liquidity.

Order flow has been found to be one of the most important microeconomic variables in exchange rate determination (Evans and Lyons 2002). It is defined as the net of buyer-initiated and seller-initiated orders and measures net buying pressure. These order flows contain private information on the net buying or net selling pressures on a particular currency. The significance of order flows was popularized with the 2001 study by Evans and Lyons. According to these authors, trades have more of an impact on prices when markets are illiquid. Thus changes in order flows are used as a signal to the market makers who in turn interpret these changes to inform their actions in the market.

Evans and Lyons (2002) assess the impact of order flows on exchange rate returns using OLS for the deutsche mark/dollar market. They assume a positive relationship between order flows and price changes and state that order flows convey information pertaining to the realization of uncertain demands that currency markets need to aggregate.[2] Results show a positive and statistically significant relationship between order flows and exchange rate changes from GARCH (1, 1) models. This is similar to the results of the OLS model by Evans and Lyons (2001). The significant effects of intervention both on order flows and in reducing exchange rates are also evident. The results of Evans and Lyons (2002) indicated the significant impact of order flows on

[2] The information pertaining to the realization of uncertain demands include differential interpretation of news, shocks to hedging demands and shocks to liquidity demand (Evans and Lyons, 2002).

changes in log returns with 60.0 per cent of the variation in the deutsche mark/dollar price changes being explained by changes in order flows.

Khemraj *et al.* (2009) apply the methodology employed by Evans and Lyons (2002) to the Guyanese foreign exchange market utilizing GARCH techniques as well as including a GARCH-based volatility of risk. This approach was utilized given the low explanatory power of the Evans and Lyons (2002) model as well as the serial correlation and heteroskedasticity present in the model when applied to the Guyanese foreign exchange market. Given that high-frequency data is characterized by significant volatility, the application of the GARCH methodology by Khemraj *et al*. (2009) is warranted. These models have also been applied by authors such as Hsieh (1988) and Baille and Bollerslev (1989) who confirm the appropriateness of GARCH models in modeling the time varying volatility inherent in foreign exchange rate data.

Hassan (2009) assesses the impact of intervention on the level and volatility of the Japanese Yen (JPY)/ USD exchange rate. He also determined the key factors that prompt the Japanese Monetary Authority (JMA) to intervene in the market utilising several GARCH models. Hassan (2009) found that the GARCH-M, Threshold GARCH and the EGARCH were the preferred models relative to the traditional GARCH. His results also showed that deviations from the monthly exchange rate target, volatility associated with exchange rate appreciations as well as the interest differential were factors that determined JMA intervention.

2.2 The Jamaican Foreign Exchange Market Studies

Microstructure studies on the foreign exchange market in Jamaica look at the effectiveness of central bank intervention in the market (Seerattan, 2006; Franscique and Lewis, 2008, Brown, 2009) as well as the current structure of the market and its implications for market stability (McFarlane, 2009). Unlike these studies, this paper seeks to determine a threshold level based on liquidity and volatility in the JMD/USD market that will prompt intervention by BOJ. It also seeks to determine the price impact of a trade by analyzing the effect of intervention on changes in the exchange rate via order flows.

Exchange markets exhibit significant volatility as highlighted by Hsieh (1988) and Baille and Bollerslev (1989). As a result, volatility models such as GARCH models have also been applied to the Jamaican market. Both Seerattan (2006) and Franscique and Lewis (2008) used GARCH techniques to model the effectiveness of intervention in the JMD/USD market.[3] These models were able to capture the inherent volatility in the market, the results, however, were mixed. Although Sereetan (2006) found that over the period October 2001 to September 2004, intervention sales were effective for the "exchange rate goals" in Jamaica, he noted that intervention was ineffective in dampening market volatility.[4] On the other hand, Franscique and Lewis (2008) identified stabilizing effects of intervention on the exchange rate over the period May 2001 to May 2008.

Franscique and Lewis (2008) used a probit model to identify the efficacy of intervention in the JMD/USD market. They determined the excessive deviation of the JMD/USD exchange rate from its 100-day moving average, a decrease in the interest rate differential, an excess demand for USD, lagged interventions, and to a lesser extent a lower NIR to imports ratio increases the likelihood of intervention.[5] Unlike Franscique and Lewis (2008), this paper used an ordered probit model to determine the parameters of an intervention reaction function, since intervention has three states (purchase, sale or no intervention).

Brown (2009) analyzed the influence of order flows on exchange rates using an OLS methodology. In particular, he analyzed the forecasted performance of order flows in predicting exchange rate changes, tests for dealer risk sharing using the Inventory-

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[3] Seerattan (2006) uses a CGARCH while Franscique and Lewis (2008) use an EGARCH.
[4] Seerattan define these exchange rate goals as the movement of the exchange rate in the desired direction. Given that the exchange rate tends to depreciate more often than it appreciates, intervention would be effective once it reduces the exchange rate.
[5] The NIR to imports ratio is known as the inventory ratio and is the ratio of the stock of foreign currency reserves to Jamaican imports. A high inventory ratio should lead to reduced sales of those reserves via a signaling effect (Franscique and Lewis, 2008).

Information model and used a vector autoregression (VAR) to determine the origin of the exchange rate variations. He also examined the effects of these order flows and BOJ's intervention on short-run volatility of the exchange rates. His study used daily data from February 2002 to January 2008 on the JMD/USD exchange rate, the US interbank LIBOR rate, local overnight interbank rates, oil prices, energy prices, as well as the net international reserves (NIR). Brown (2009) found that the explanatory power of the exchange rate volatility increased when trade flows were included in the OLS model, but noted the poor forecast power in periods of high volatility. He also noted that the market-wide impact of order flows on inter-dealer trading was significant. Finally, Brown (2009) found that there was private payoff-relevant information in customer trades resulting from the sustained cumulative exchange rate volatility after a trade flow shock.

McFarlane (2009) investigated the current structure of the foreign exchange market in Jamaica in an attempt to understand the viability and stability of the market. She tested for market efficiency by taking a market microstructure approach and used empirical measures of arbitrage returns, price dispersion and serial correlation and found that the market was inefficient. McFarlane (2009) noted that these inefficiencies had the potential to lead to trading halts and excess volatility in the market if left unattended. She therefore proposed measures that would improve market efficiency such as the use of an electronic trading platform for the market.

3.0 The Foreign Exchange Market - Measures of liquidity and volatility

The JMD/USD foreign exchange market has experienced frequent periods of turbulence particularly in the last decade, of which the effects on the exchange rate have been permanent. During these periods, there were occasions when the BOJ intervened in the foreign exchange market to stabilize the Jamaica Dollar. In the first two quarters of 2003 there was significant depreciation in the Jamaica Dollar vis-à-vis the US Dollar. This depreciation was largely influenced by a fall in market confidence triggered by deterioration in the balance of payments and fiscal accounts as well as a downgrade by Standard and Poors (S&P) on Jamaica's sovereign rating. The sharp depreciation resulted in increased demand for foreign currency assets and, consequently, high levels of JMD liquidity (QMPR, 2003a; 2003b; 2004). Similar sharp depreciations in the exchange rate occurred in 2005 and 2008. The 2005 depreciation was influenced by monetary tightening in the US resulting in a portfolio shift as reflected in reductions in net private capital flows.[6] There were also concerns about the heightened domestic inflation, impacted by increases in international crude oil prices, which contributed to a fall in investor confidence (QPMR 2005a; 2005b). In 2008, the global financial crisis resulted in margin calls from external counterparties and the closing out of repo arrangements held primarily by local securities dealers as well as the termination or reduction of credit lines to domestic institutions all of which put increasing pressure on the value of the Jamaica Dollar (QMPR, 2009). The effects of this continued into 2009. More recent in April 2010, the JMD appreciated against its US counterpart largely due to the Government's Jamaica Debt Exchange (JDX) initiative as well as the approval of International Monetary Fund Stand-By Arrangement. Both events have led to increased confidence in market conditions resulting in the noted appreciation in 2010 (QMPR, 2010).

There have also been other cases of BOJ intervention which aimed to reduce the magnitude of changes in the value of the Jamaican Dollar. For the sample period under review, January 2001 to June 2010, the Bank intervened in the foreign exchange market a total of 494 times with an amount totaling approximately US$6 374.29 million. In light of this, and based on the mixed results of previous research examining the efficacy of BOJ's intervention, the question arises as to the signals BOJ uses to inform the timing of intervention in the JMD/USD market. Illiquidity in the market can be seen as a signal for pending intervention since, for example, a shortage in supply of or excess demand for USD increases the willingness of end users to pay a higher price for the financial asset. This in effect results in depreciation in the value of the Jamaica Dollar.

In order to analyze periods of illiquidity it is best to determine actual liquidity in the market. This can be done using several measures elaborately explored in the literature

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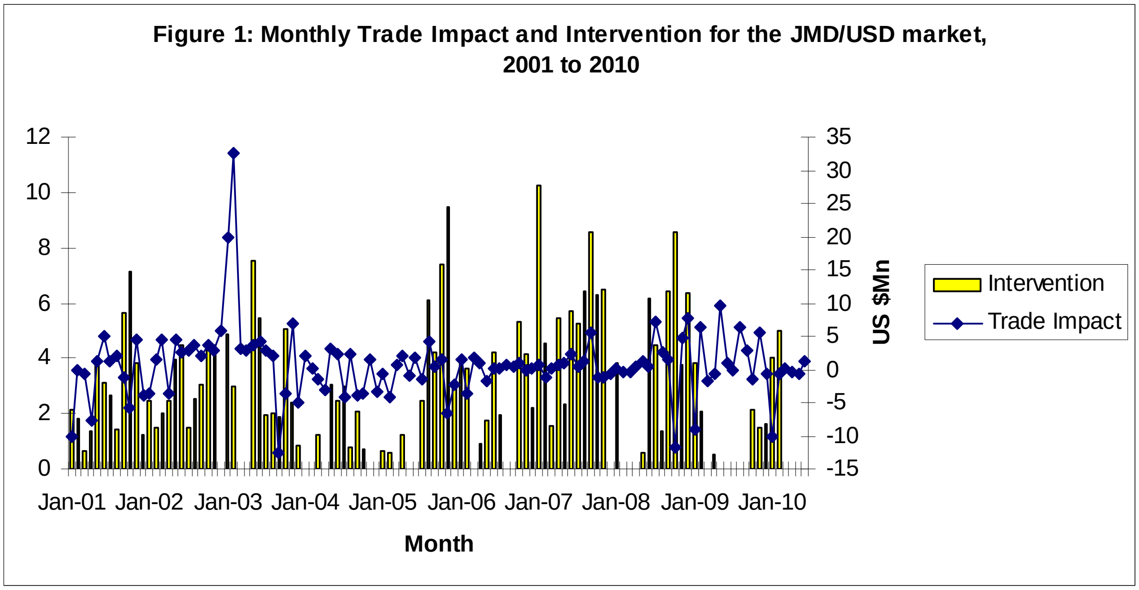
[6] In 2005, the United States tightened their monetary policy by increasing interest rates which increased concerns about the real returns on Jamaica Dollar assets vis-à-vis US assets.

and applicable to financial assets. However, given the lack of depth and the thinness of the foreign exchange market in Jamaica, standard liquidity measures in the literature may have different implications for Jamaica. Monthly data for the JMD/USD is used to measure liquidity because of low trading frequencies. Following Mancini *et al*. (2010), the return reversal, bid ask spreads, return volatility and the trade impact coefficient will also be used as measures of liquidity.

Applying the reasoning of Campbell *et al*. (1993), return reversal is said to occur when net buying (selling) pressures on an illiquid currency results in an excessive depreciation (appreciation) followed by a reversal to its fundamental value. Liquidity for a given month therefore represents the average effect on returns for day *t* given the volumes traded on day *t-1*. It is also assumed that the previous day's signed volume (a measure of order flow) is given the same sign as the previous day's return and therefore lower liquidity is reflected in large price changes on day *t* in the opposite direction of the order flow at time *t-1* (Pastor and Stambaugh, 1993). In this context, a positive relationship between current order flows and current returns is anticipated. In the same vein, a negative relationship between lagged order flows and current returns is anticipated. This is illustrated in the model as follows:

$$\Delta P_t = \phi_t + \varphi_t(V_{b,t} - V_{s,t}) + \gamma_t(V_{b,t-1} - V_{s,t-1}) + \varepsilon_t \qquad [1]$$

where ΔP_t represents the monthly currency returns on JMD/USD trades, $V_{b,\ t} - V_{s,\ t}$ represents the contemporaneous order flows, with $V_{b,\ t}$ indicating purchase volumes and $V_{s,\ t}$ represents sales volumes. A positive value for order flows indicates net purchases of USDs and a negative value indicates net sales of USDs. The coefficient γ_t represents the measure of liquidity based on return reversal and is expected to be negative. The more liquid a currency, the smaller the temporary price change accompanying order flow (Mancini et al, 2010). Contemporaneous order flows are assumed to contain information on the value of a currency due to the fact that they provide private information to the market. In this sense, the coefficient on the contemporaneous order flows, φ_t, represents the trade impact and refers to the degree of asymmetric information in the market. Larger trade impact coefficients indicate that the degree of asymmetric information in the market is great (Mancini *et al.*, 2010). Based on this premise, trade impact coefficient is expected to be positive. [7] This is due to the fact that a net purchasing order flow impacts positively on foreign exchange returns (Evans and Lyons, 2002).

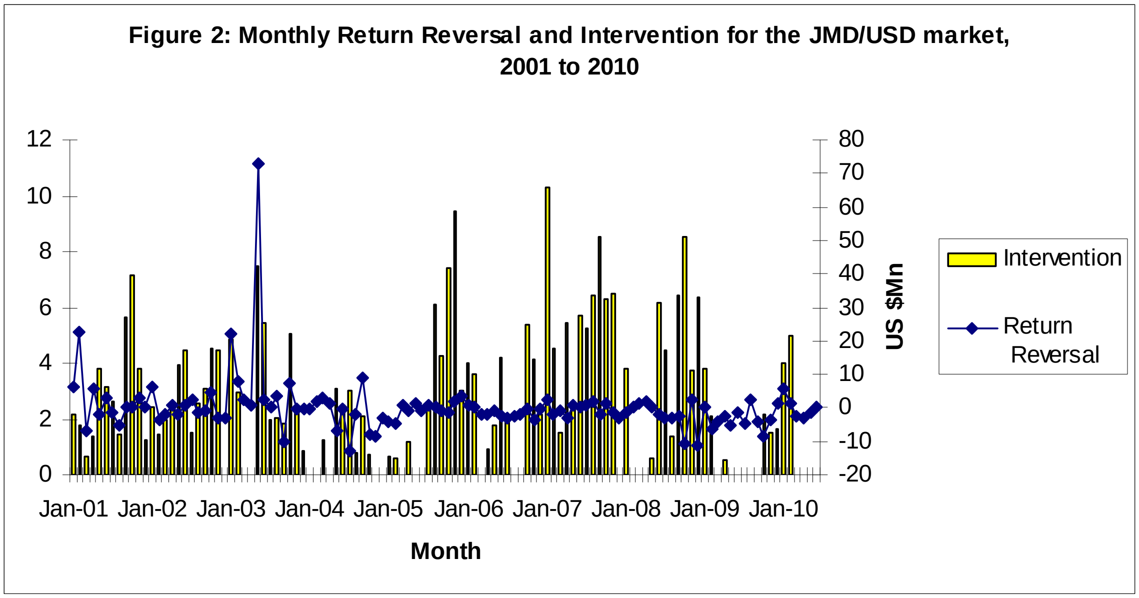


Source: The Bank of Jamaica.

A priori expectations hold that the trade impact coefficient should be positive signaling the importance of net buying/selling pressure on the exchange rate. This is not the case for the JMD/USD foreign exchange market as the results indicate both positive and negative values for the trade impact coefficient over the period (see Figure 1). The trade impact coefficient was able to adequately reflect the volatile periods in the JMD/USD foreign exchange market for 2003, 2005, 2006, and 2008. Within the sample period, the BOJ intervened during the volatile periods during 2003, 2008 and the first

[7] For a detailed analysis of the relationship between returns, contemporaneous and lagged order flows, see Mancini, Ranaldo and Wrampelmeyer (2010).

quarter of 2009. There was no intervention between March and September 2009 which was a period where some amount of illiquidity was evident.[8]



Source: The Bank of Jamaica.

The results from equation [1] for return reversal are inconsistent with the *a priori* expectations. Similar to the trade impact coefficient, the return reversal coefficient takes on both positive and negative values over the period (see Figure 2). The return reversal coefficient, however, reflected the illiquidity in the market during 2003 with a significant spike occurring in May of that year. The paper also provides a further breakdown of the return reversal which highlights the illiquidity in the market during 2008 and 2009 (see Figure A.7 in Appendix A).

The quoted bid-ask spread has been used as a measure of liquidity by Chordia *et al*. (2001) and Mancini *et al*. (2010).[9] However data restrictions preclude the usage of the

[8] For a break down of the period by sub-sample, see Figures A.4 and A.5 in Appendix A.
[9] The quoted bid ask spread is the difference between the lowest ask price and the highest bid price.

quoted bid-ask measure. Instead, for this analysis, the bid-ask spread is used, and is computed as the difference between ask and the bid prices. Using this measure, liquidity is prevalent in a market where the bid-ask spread is low. Thus, high spreads are indicative of illiquidity and are therefore a cause for concern. It is important to note, however, that Chordia *et al.* (2001) utilized this measure of liquidity in their analysis of stock markets. Applying the quoted spread to the foreign exchange market, Mancini *et al.* (2010) noted a major drawback of this measure as being the fact that "deals frequently transact at better prices, deeming quoted spread measures inappropriate for an accurate assessment of execution costs" (Mancini *et al*., 2010, p. 11). Nevertheless, a variation of this measure will be utilized as one of several measures of liquidity and as such will not be the sole indicator upon which liquidity in the market is assessed.

In particular, the quoted bid-ask spread is calculated as the difference between the ask price and the bid price divided by the mid-quote as follows[10]:

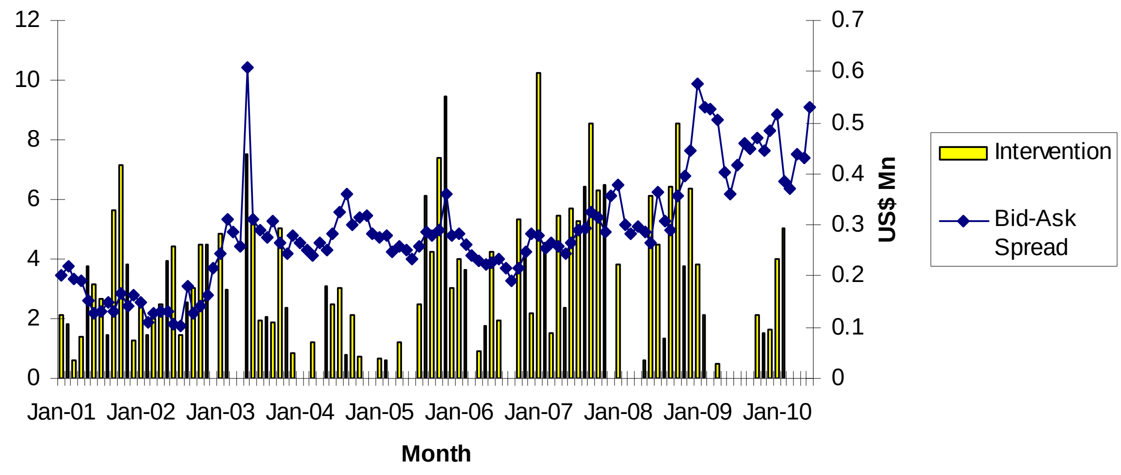
$$S_t = \frac{P_{A,t} - P_{B,t}}{P_M} \qquad [2]$$

However, for the purpose of this analysis, the bid-ask spread calculated as the difference between the ask price and the bid price is used. This spread computation is outlined as follows:

$$S_t = P_{A,t} - P_{B,t} \qquad [3]$$

[10] Chordia, Roll and Subrahmayam (2001) refer to this measure as the percentage quoted spread.

Figure 3: Monthly Bid-Ask Spread and Intervention for the JMD/USD market, 2001 to 2010



Source: The Bank of Jamaica.

The average monthly bid-ask spread for the period January 2001 to June 2010 has exhibited an upward trend starting the period with a low of 0.199 and ending the period with 0.522 (see Figure 3). This is an indication of the reduction in liquidity throughout the period. The bid-ask spread was at its highest during 2003 signaling significant illiquidity in that period. This was brought on by an increase in demand for US dollars against a background of deteriorating fiscal balances, balance of payments, and investor confidence. The bid-ask spread peaked again in 2009 when both low US dollar supply and high demand for US dollars along with weakened fundamentals in the macroeconomy led authorized dealers to widen their spreads.[11]

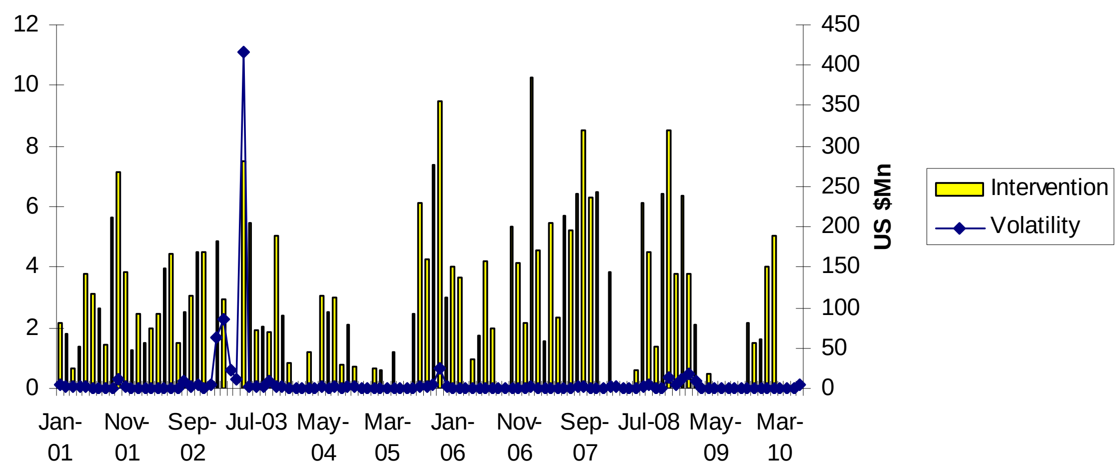
Foreign exchange returns is calculated as the difference between the mid-quote for day *t* and the mid-quote for day *t-1*. It is calculated as follows:

$$R_t = \left[\frac{P_M - P_{M-1}}{P_{M-1}}\right] \qquad [4]$$

[11] For a breakdown of the bid-ask spread by sub-period, see Figures A.8 and A.9 in Appendix A.

Volatility in the market increases the demand for higher compensation by market makers due to the additional risk they face (Mancini *et al*., 2010). As such, there is a negative relationship between volatility and liquidity in the foreign exchange market.[12]

Figure 4: Monthly Volatility and Intervention for the JMD/USD market, 2001 to 2010



Source: The Bank of Jamaica

The average monthly return volatility for the period January 2001 to June 2010 highlights the periods over the sample when activity in the foreign exchange market was more volatile than normal (see Figure 4). It appears that from this measure, the JMD/USD foreign exchange market for the most part was liquid over the period. However, an analysis of the two sub-periods indicates excess illiquidity in 2003, 2005, 2008 and 2009. It also indicates some movement in the latter part of the period.

Overall the four measures of liquidity highlight the lack of accessible funds in the market were not without significant price impact for the years 2003, 2005, 2008 and 2009. Although the specific months varied across the different measures, they all captured the idiosyncrasies present in the market. Given these measures, it is important to assess the timing of intervention by the BOJ.

[12] Returns volatility is calculated as the square of daily foreign exchange returns.

4.0 Modeling the Price Impact of Trade

4.1 Data Description and Empirical Model

Daily data was gathered on the foreign exchange transaction volumes and exchange rates for the JMD/USD market from January 2, 2001 to June 30, 2010. This data differs from Evans and Lyons (2001) as the authors used high frequency intraday data as opposed to daily data.

Studies of the price impact of trade model the influence of order flows and the information they contain on the changes in exchange rates for several currency pairs (Evans and Lyons, 2002 and Khemraj *et al.*, 2009). This paper uses the model used by Evans and Lyons (2001) to model the price impact using OLS as follows:

$$\Delta P_t = (\beta_1 + \beta_2 A_t)x_t - \beta_3 \Delta P_{t-1} + \varepsilon_t^p \qquad [5]$$

$$x_t = \beta_4 x_{t-1} + \beta_5 \Delta P_{t-1} + \varepsilon_t^x; \quad x_t = V_{b,t} - V_{s,t} \qquad [6]$$

where ΔP_t represents the monthly currency returns on JMD/USD trades, x_t represents the changes in contemporaneous order flows, x_{t-1} represents the changes in lagged order flows and A_t represents central bank intervention. The first term in equation [5] represents the price impact of order flow and is greater when the order flows is preceded by central bank intervention. The second term represents the mean reversion of prices as a result of previous order flow-price effects. According to Evans and Lyons (2001) this reflects the transitory risk premia in the model. In equation [6], the first term represents interdealer trading in the market which is expected to be positive as dealers pass their positions across the market to manage their risks. This is an illustration of hot potato trading, which is also positively related to past returns.

Given the possible ARCH effects present in exchange rate data (see Khemraj *et al.*, 2009) a GARCH (1, 1) will be estimated. The general form of the conditional variance equation for the GARCH (1, 1) is:

$$h_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta h_{t-1}^2 \qquad [7]$$

where h_t^2 is said to be well defined if $\alpha_1 + \beta < 1$. Thus the mean equation from [5] is used to estimate volatility.

Applying other alternative estimation procedures based on Evans and Lyons (2001), both non-parametric techniques and impulse response functions were utilised to determine the price impact of trades. This non-parametric model takes the following form:

$$\Delta P_t = \pi(x_t, \Delta P_{t-1}, s_{t-1}) + \varepsilon_t^p \qquad [8]$$

$$x_t = \mu(x_{t-1}, \Delta P_{t-1}, s_{h-1}) + \varepsilon_t^x \qquad [9]$$

where $\pi(.)$ and $\mu(.)$ are fixed, unknown and non-linear factors of the variables, s_{t-1} is a vector of state variables and ε_t is the error term. For the purpose of this analysis lagged interventions, lagged volatility as well as lagged trade volumes will also be used as state variables.

5.0 Liquidity, Volatility and Intervention

5.1 Data Description and Empirical Model

This section models the factors that determine the probability of intervention following Hassan (2009). For all variables excluding the interest differential, the daily data is used for the period January 2, 2001 to June 30, 2010. Daily data is used to calculate the interest differential for the period June 9, 2005 to June 30, 2010. The order flow variable will be used as the measure of liquidity for the purpose of this analysis while the volatility measure is derived from the GARCH (1, 1) outlined in Section 4. An ordered probit model will be employed to address the issues that arise when a dependent dummy variable, intervention, is modeled. The ordered probit model estimated in this paper involves the specification of three separate distributional assumptions for the intervention series which correspond to the three different states of intervention outcome.

Intervention has three types of events; "buying intervention", "selling intervention" and zero intervention. The central bank is assumed to react to market conditions and constraints defined by the explanatory variables of the model beyond a particular threshold level. These threshold levels are estimated by maximizing a likelihood function and may differ for buying or selling of foreign currency (Hassan 2009). The precise form of the ordered probit model is outlined in equation (10).

$$\begin{aligned} Int_t = \beta_1 Int_{t-1} + \beta_2 \Delta P_{t-1} + \beta_3 x_t + \beta_4 (h_{t-1})(Ddepr_{t-1}) \\ + \beta_5 (h_{t-1}(Ddepr_{t-1})(Dsize_{t-1}) + \beta_6 (i_{t-1} - i^*_{t-1}) + \varepsilon_t \end{aligned} \qquad [10]$$

where Int_t is a dummy variable that takes the value of one if there is a sell intervention, negative one if there is a buy intervention and zero if no intervention, ΔP_{t-1} represents the previous day's price change in the JMD/USD exchange rate, h_{t-1} represents the lagged conditional variance of daily exchange rates changes from the GARCH (1, 1) model estimated in equation [7] for the price impact mean equation [5], $Ddepr_{t-1}$ is a dummy variable that takes a value of one if the JMD depreciates against the USD and zero otherwise, $Dsize_{t-1}$ is the dummy variable that takes the value one if the size of the measured volatility exceeds the average level for the sample period and zero otherwise, and $i_{t-1} - i*_{t-1}$ represents the interest rate differentials which is the difference between the Jamaican inter-bank overnight interest rate and the US Federal funds rate.[13]

Intervention occurs once the right hand side of equation [10] defined as *f (.)* without the error term, falls above or below particular threshold values. It is assumed that:

$$IINV_t = 1 \qquad \text{if} \qquad f(\cdot) > \theta^+$$

$$IINV_t = 0 \qquad \text{if} \qquad \theta^- \le f(\cdot) \le \theta^+$$

[13] It is important to note that the interest rates are the only macroeconomic variable available at a daily frequency.

$$IINV_t = -1 \quad \text{if} \quad f(\cdot) < \theta^-$$

where $IINV_t$ is the dependent variable and θ^+ (>0) and θ^- (<0) are the thresholds above which the central bank acts to sell or buy USD, respectively. $IINV_t$= 1 if there was a sale intervention in the JMD/USD market, $IINV_t$= -1 if there was a purchase intervention in the JMD/USD market and INV_t = 0 if the there was no intervention.

To arrive at these threshold values, the following likelihood function for equation [10] is maximized:

$$L = \prod_{IINV>0} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(IINV+\theta^+ - X\Omega)^2}{2\sigma^2}} * \prod_{IINV=0} \{\Phi(\frac{\theta^+ - X\Omega}{\sigma}) - \Phi(\frac{\theta^- - X\Omega}{\sigma})\} * \prod_{IINV<0} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(IINV+\theta^- - X\Omega)^2}{2\sigma^2}}$$

where Φ is the standard normal cumulative density function.

6.0 Results

6.1 Ordinary Least Squares (OLS)

This paper applies the Evans and Lyons (2002) model to the JMD/USD market using daily data over the period 2 January 2001 to 30 June 2010. The OLS regression for the price impact equation showed lagged price changes to be positive and statistically significant (see Table 1a). Therefore a one unit ($) change in past prices affects future price changes by $0.38. This is contrary to Evans and Lyons (2001) who state that for mean reversion, there is a negative relationship between lagged and current price changes. The results of the paper therefore implies that mean reversion does not occur. On the other hand, contemporaneous order flows as well as the interaction variable were found to be positive and statistically insignificant and have no impact on price changes.

A significant positive relationship exists between lagged and current order flows based on the OLS model of equation [6] (see Table 1b). Thus a one unit ($) change in past order flow increases current order flows by $0.16. This provides evidence of hot potato trading which implies that interdealer trades are passed from dealer to dealer for risk management purposes. On the contrary, lagged price changes were found to be statistically insignificant at the relevant levels.

Table 1a: Regression Results - Ordinary Least Squares (OLS) for the Price Impact of Trade in the JMD/USD market

Linear Model: $\Delta P_t = (\beta_1 + \beta_2 A_t)x_t - \beta_3 \Delta P_{t-1} + \varepsilon_t^p$

Equation	x_t	$x_t A_t$	ΔP_{t-1}	R^2
(i)	7.31e-10	1.25e-09	0.376*	0.13
	[0.2612]	[0.5518]	[0.003]	
(ii)	1.11e-09	1.22e-09		-0.008
	[0.1283]	[0.5051]		
(iii)	9.15e-10***		0.377*	0.135
	[0.1617]		[0.004]	
(iv)		1.98e-09	0.377*	0.134
		[0.3343]	[0.0033]	
(v)	1.29e-09***			-0.008
	[0.0538]			
(vi)		2.33e-09		-0.009
		[0..1661]		
(vii)			0.378 *	0.134
			[0.0033]	

Notes: p-values are presented in parentheses with robust standard errors used to correct for heteroskedasticity. *, ** and *** represents the 1per cent, 5 per cent and 15 per cent, respectively.

Table 1b: Regression Results - Ordinary Least Squares (OLS) Hot Potato Trading in the JMD/USD market

Linear Model: $x_t = \beta_4 x_{t-1} + \beta_5 \Delta P_{t-1} + \varepsilon_t^x$

Equation	x_{t-1}	ΔP_{t-1}	R^2
(i)	0.162*	1144536	-0.020
	[0.000]	[0.1377]	
(ii)	0.163*		-0.002
	[0.000]		
(iii)		1445259*	-0.047
		[0.0640]	

Notes: p-values are presented in parentheses with robust standard errors used to correct for heteroskedasticity. *, ** and *** represents the 1per cent, 5 per cent and 15 per cent, respectively

6.2 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

As previously stated, OLS does not take into account the volatility clustering present in high frequency exchange rate data. White's heteroskedasticity test was carried out on the OLS model and indicated the presence of heteroskedasticity. To correct for this, the OLS model was re-estimated using White's robust standard errors. This however, did not correct the time-varying volatility problem. ARCH tests confirmed the presence of ARCH effects in the model and as such a GARCH (1, 1) model was estimated using equation [7] to account for heteroskedasticity. More specifically, the GARCH (1, 1) model was used to estimate the impact of order flow on changes in exchange rates as well as hot potato trading. For the price impact of a trade, all three variables were found to be statistically significant (see Table 2a). Customer order flows impacted positively on exchange rate changes while the interaction between intervention and order flows as well as lagged price changes impacted negatively on price changes. The interaction variable in particular is important since it indicates that BOJ interventions have been able to reduce the change in exchange rate.

With respect to hot potato trading (Table 2b), only the lagged order flows were found to be positive and statistically significant and implies that currency positions are passed from trader to trader. On the other hand, lagged exchange rate changes were positive but statistically insignificant.

Table 2a: Regression Results – GARCH (1, 1) for the Price Impact of Trade in the JMD/USD market

Linear Model: $\Delta P_t = (\beta_1 + \beta_2 A_t)x_t + \beta_3 \Delta P_{t-1} + \varepsilon_t^p$

GARCH Model: $h_t = \phi + \alpha u_{t-1} + \beta h_{t-1}$

Equation	x_t	$x_t A_t$	ΔP_{t-1}	R^2	α	β
(i)	4.70e-10** [0.0274]	-1.08e-09** [0.0002]	-0.086*	-0.086	0.267 (0.0139)	0.744 (0.0085)
(ii)	4.22e-10*** [0.0472]	-9.70e-10** [0.0549]		-0.012	0.263	0.748
(iii)	3.49e-10* [0.0731]		-0.083* [0.0002]	-0.082	0.264	0.747
(iv)		-6.14e-10 [0.1764]	-0.083* [0.0004]	-0.083	0.268	0.743
(v)		-5.56e-10 [0.2310]		-0.011	0.264	0.748
(vi)	3.15e-10 [0.1067]			-0.009	0.261	0.751
(vii)			-0.082* [0.0003]	-0.079	0.266	0.745

Notes: p-values are presented in parentheses with robust standard errors used to correct for heteroskedasticity. *, ** and *** represents the 1per cent, 5 per cent and 10 per cent, respectively.

Table 2b: Regression Results - GARCH (1, 1)
Hot Potato Trading in the JMD/USD market
Linear Model: $x_t = \beta_4 x_{t-1} + \beta_5 \Delta P_{t-1} + \varepsilon_t^x$
GARCH Model: $h_t = \phi + \alpha u_{t-1} + \beta h_{t-1}$

Equation	x_{t-1}	ΔP_{t-1}	R^2	α	β
(i)	0.159*	1103156	-0.021	0.028	0.970
	[0.000]	[0.2098]			
(ii)	0.155*		-0.021	0.027	0.970
	[0.000]				
(iii)		1195521	-0.048	0.030	0.968
		[0.1709]			

Notes: p-values are presented in parentheses with robust standard errors used to correct for heteroskedasticity. *, ** and *** represents the 1per cent, 5 per cent and 10 per cent, respectively.

6.3 Vector Autoregression (VAR) Model

A VAR model was estimated using the time varying coefficients from a non-linear model consisting of lagged price changes, volatility, and lagged values of sales and purchase volumes. These time-varying coefficients were derived from the non-linear model in equation [8] since the item of interest is with the price impact of a trade and to a lesser extent the prevalence of hot potato trading. This is important given the restrictions of the OLS and GARCH (1, 1) models estimated in the previous sections. In particular, both models estimate a constant coefficient for each variable. For the purposes of the analysis, however, it was deemed important to assess the coefficients of the variables across time to determine the trend. Thus a state-space model was used to estimate the respective time-varying coefficients.

Impulse response functions (IRFs), based on the VAR model, were derived to trace out the effects of any shocks to a particular variable on exchange rate movements.[14] From the IRFs, the effect of a one standard deviation (s.d.) shock to lagged price changes to itself dies out after approximately eight days. On the other hand, a one s.d. volatility shock reduces the price change after four days and increases price changes between

[14] The graphs are outlined in Figures B.1 to B.4 in Appendix B.

periods five and seven. The effect of the volatility shock on prices dies out after approximately thirteen periods. A one unit shock to both logged sales and purchase volumes significantly impacts on price changes since they die out after approximately thirty periods. The impulse response functions therefore illustrate the importance of trade volumes in affecting future price changes.

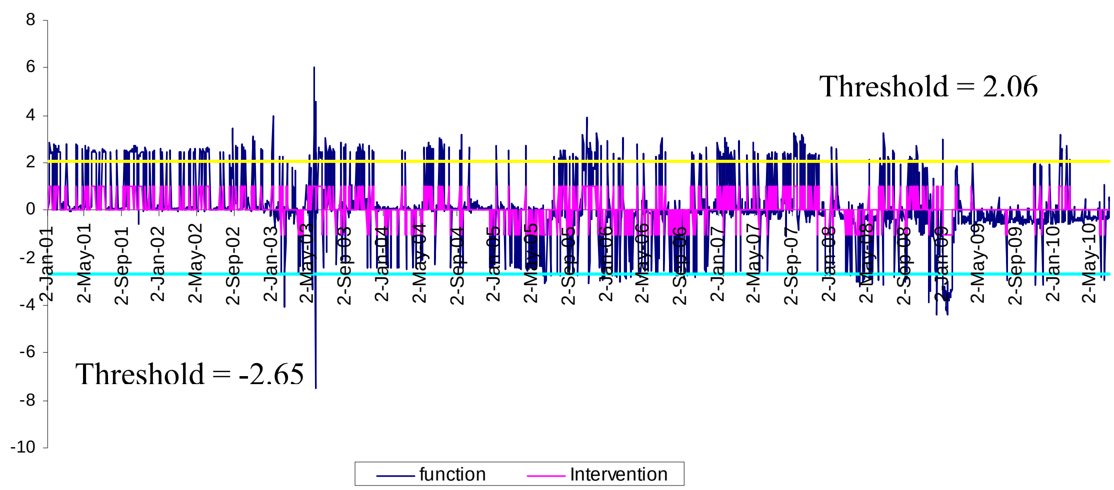
Based on the variance decompositions, a shock to lagged price changes contributed approximately 98.0 per cent to its own adjustment. With respect to the other variables, lag purchase volumes and past volatility had the greatest impact on past price changes. The previous day's sales volumes were found to have the least effect on past price changes.

6.3 Ordered Probit Model

The results of the ordered probit model suggest that there is asymmetry in the intervention reaction function. Of note, in maximizing the likelihood function of the ordered probit, a threshold of 2.06 standardized units was determined for depreciation, while a threshold of -2.65 standardized units was estimated for appreciation. The results show that the Bank actually intervened when the reaction function signaled intervention, based on the respective threshold levels for depreciation and appreciation (see Figure 5).[15] However, for closer analysis, the sample was split into two sub-periods: January 2001 to December 2004 as sub-period 1; and January 2005 to June 2010 as sub-period 2 (see Appendix for respective graphs in Figures B.5 and B.6). Of note, while the Bank actually intervened when there were signals on the sell side, there were sufficiently more periods of no signals on the purchase side when the Bank actually intervened. This is an important result and has possible strong implications for policy.

[15] A signal for intervention occurs when the reaction function exceeds (in absolute terms) the threshold values.

Figure 5: Intervention, the reaction function, and threshold levels



7.0 Policy Implications

The conduct of foreign exchange market intervention, in practice, requires the development of a comprehensive set of policies and guidelines on a wide range of operational issues at the policy, technical, and administrative levels. At the policy level, decisions must be made on the objectives of intervention, the criteria for determining the amount and timing of intervention, and the degree of transparency.

There is no simple rule for determining the amount and timing of intervention. It is a highly subjective exercise based on several factors, including the nature and duration of shocks, observable market indicators, market intelligence, and available reserves. However, based on the findings in this paper, some guiding principles for policymakers are provided. Although a long-term dedication to an intervention policy is not necessary when a commitment already exists to another nominal anchor such as price stability, policymakers should monitor a combination of market indicators and intelligence before making intervention decisions. Market intelligence - including information on the underlying sources of foreign exchange demand and supply, large customer transactions, order flow, and the market's view of the balance of payments outlook – is a critical complement to observable market indicators. Market intelligence gathered from players in the market would enable the BOJ to obtain critical but unobservable (on a real time basis) determinants of the exchange rate.

Determining the timing of intervention is subjective and judgmental. It involves an analysis of observable market indicators and available market intelligence against the background of the Bank's unique experiences and country specific circumstances. The primary objective of this paper is to signal the timing of intervention based on volatility and liquidity in the market. However, this is just one of the many indicators that the Bank can employ to inform that decision. The timing of intervention ultimately depends on the Bank's assessment of the presence of exchange rate misalignment and disorderly market.

Despite a voluminous amount of literature on exchange rate misalignment for Jamaica, most recent of which is Robinson (2010), there is no consensus on a methodology to compute the equilibrium exchange rate. Readily available indicators that can uncover signs of exchange rate misalignment include the nominal and real effective exchange rates, productivity and other competitiveness indicators, the terms of trade, the balance of payments and interest rate differential. However, these indicators often do not allow policymakers to identify the presence or magnitude of misalignment precisely enough to justify intervention.

Distinguishing disorderly markets from normal market dynamics and setting predetermined trigger points for intervention is extremely difficult. The lack of consensus on determinants of exchange rates at high frequency heightens the challenge of ascertaining market conditions. Trends in volatility, spreads and turnover can only be interpreted in a context of events and shocks that might be driving them. For example, volatility that amounts to market disturbance in one market can be typical behavior in another market. As such it is difficult to determine when volatility and spreads are excessive and turnover inadequate enough to warrant intervention. The challenge is compounded by the constantly changing nature of shocks to the economy and of market dynamics, including the growing diversity of market participants. Nonetheless, the BOJ should set benchmarks for various market indicators to enhance its capacity to developments, when needed.

To the extent that some degree of flexibility exists within the day (or possibly week) in terms of timing, intervention should occur in a liquid market. When the market is illiquid, intervention may have a large price impact, and/or disrupt trading conditions. Dominguez (2003) notes that interventions during heavy trading volume and closely timed to scheduled macroeconomic announcements are the most likely to have large and long-lasting effects.

8.0 Summary

This paper sought to develop measures of liquidity in the JMD/USD foreign exchange market in an effort to properly identify periods of market illiquidity. It also modeled the effect of order flows and BOJ intervention on exchange rate changes using several techniques. Finally, it modeled the factors that determine BOJ intervention using an ordered probit model. The threshold values derived from maximizing the ordered probit model suggests that on average the Bank intervened when it should have. However, results from the GARCH (1,1) model indicates that intervention, although statistically significant, had a very minimal effect on volatility. In essence, the empirical results suggest that the Bank's intervention have had a fairly limited impact on the exchange rate. In fact, when there is excess volatility in the market, interventions did not manage to halt or reverse the trend of the JMD/US except for very short periods. There were, however, instances when the Bank managed to influence market makers which correlate positively with longer adjustments in the exchange rate.

The empirical evidence also indicates that interventions have tended to positively impact volatility rather than dampen it. The limited success can be attributed to the fact that the BOJ's interventions are in effect sterilized.[16] These findings are consistent with international experience which suggests that the effects of sterilized interventions on

[16] Sterilised intervention occurs when the change in liquidity that intervention causes is almost automatically readjusted through changes in the demand for repo contracts at the Bank.

exchange rates are generally fairly limited and short-lived. It is suggested that for policy purposes the use of an ordered probit model is employed to aid in informing the timing of interventions.

References

Baille, R. T., and Bollerslev T., 1989. The Message in Daily Exchange Rates: A Conditional Variance Tale, Journal of Business and Economic Studies 7, 297- 305.

Brown, B., 2009. A Market Microstructure Analysis of Foreign Exchange Intervention in Jamaica, Bank of Jamaica working paper

Campbell, J. Y., Grossman, S. J., and Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns, The Quarterly Journal of Economics 108(4), 905–939.

Chordia, T., Roll, R., and Subrahmanyam, A., 2001. Market Liquidity and Trading Activity, Journal of Finance 56(2), 501–530

Evans, M. D. D., 2005. Foreign Exchange Market Microstructure, Georgetown University and NBER [Accessed June 17 from http://www9.georgetown.edu/faculty/evansm1/wpapers_files/tour.pdf]

Evans, M. D. D. and Lyons, R. K., 2002. Order flow and exchange rate dynamics, Journal of Political Economy, 110: 170-180.

Evans, M. D. D. and Lyons, R. K., 2001. Time-Varying Liquidity in Foreign Exchange, Georgetown University and NBER

Frankel, J., and Froot, K., 1990. Chartists, fundamentalists, and trading in the foreign exchange market, American Economic Review 80, 181-185.

Franscique, L. and Lewis, J., 2008. An Assessment of the Effectiveness of Bank of Jamaica Intervention in the Foreign Exchange Market between 2001 and 2008, Bank of Jamaica working paper

Grossman, S. J. and Miller, M. H., 1988. Liquidity and Market Structure, The Journal of Finance 43(3), Papers and Proceedings of the American Finance Association, Chicago, Illanois, December 28-30, 1987, 617-633

Hassan, M., 2009. A Comprehensive Study on the Japanese Foreign Exchange Intervention in the JPY/USD exchange market [Accessed July 12, 2010 from http://web.gc.cuny.edu/economics/SeminarPapers/spring%202009/Japan_core_paper_May09.doc]

Hseih, D.A., 1988. Modeling the Heteroscedasticity in Daily Exchange Rates, Journal of Business and Economic Statistics, 7, 307-317.

Mancini, L., Ranaldo, A., and Wrampelmeyer, J., 2010. Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums, Swiss National Bank Working Paper

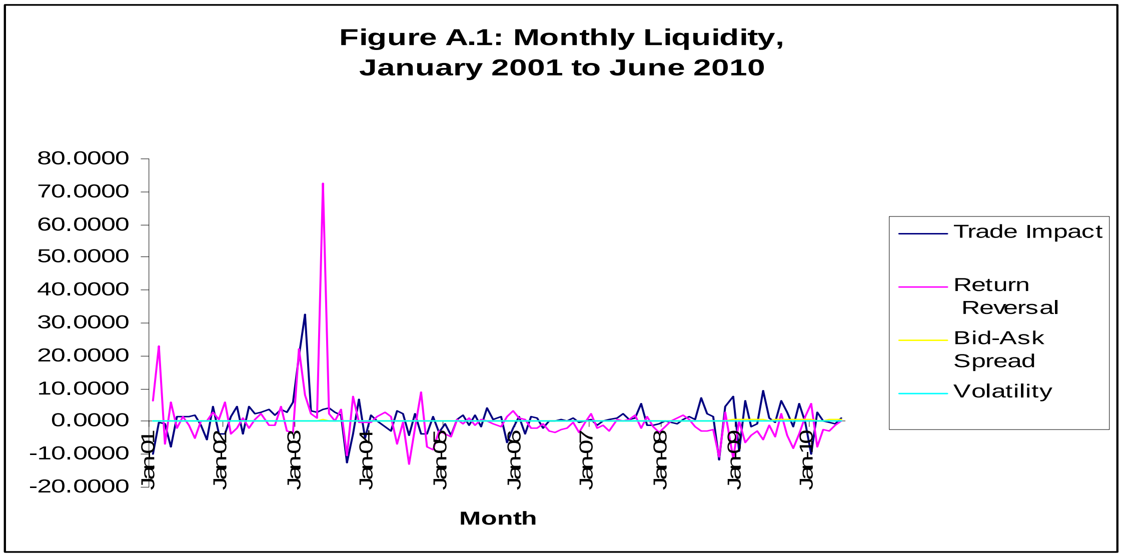
McFarlane, L., 2009, The future of the Jamaican foreign exchange market: A market microstructure perspective, Bank of Jamaica Working Paper

Pastor, L., and Stambaugh, R. F., 2003. Liquidity Risk and Expected Stock Returns, Journal of Political Economy, 111(3), 642–685.

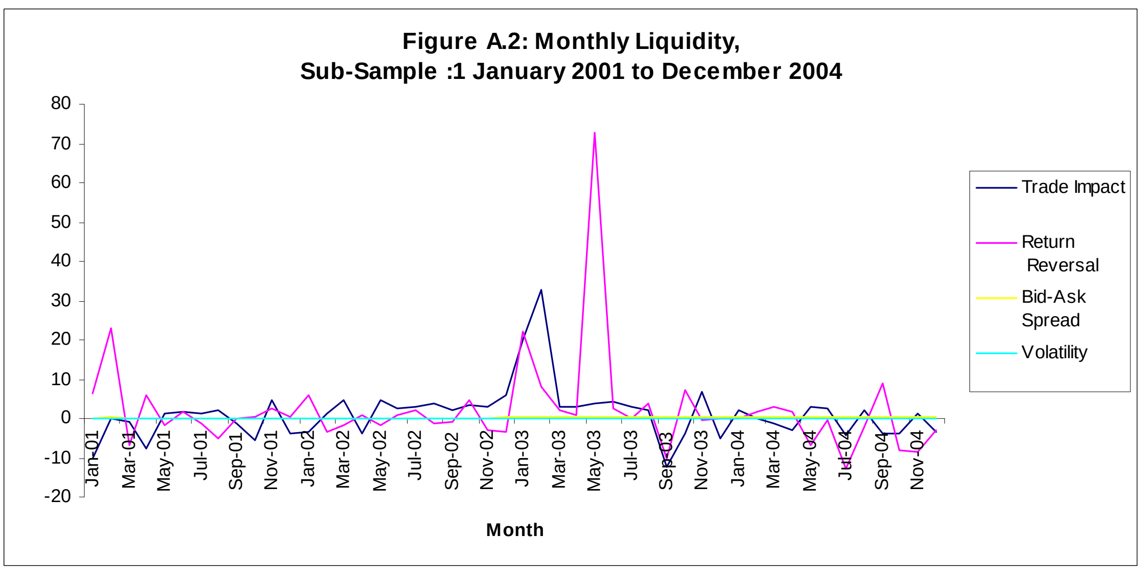
QMPR (various issues), Bank of Jamaica, Quarterly Monetary Policy Report.

Seerattan, D., 2006. The Effectiveness of Central Bank Intervention in the Foreign Exchange Markets in Select Flexible Exchange Rate Countries in the Caribbean, Business, Finance and Economics in Emerging Economies, 1(1).

Appendix



Source: The Bank of Jamaica



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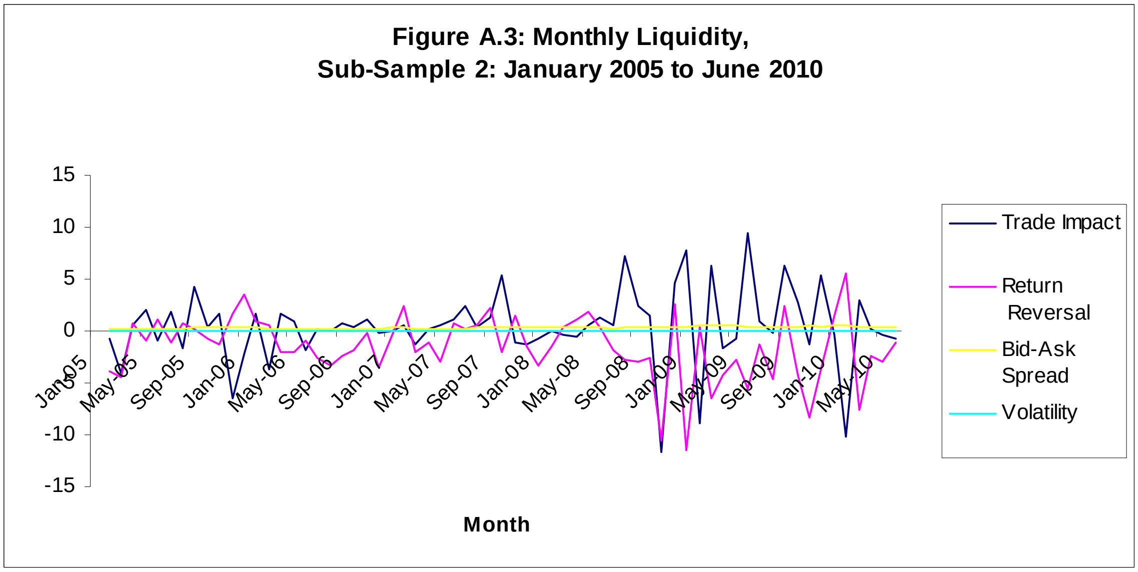


Figure A.3: Monthly Liquidity,
Sub-Sample 2: January 2005 to June 2010

Source: The Bank of Jamaica

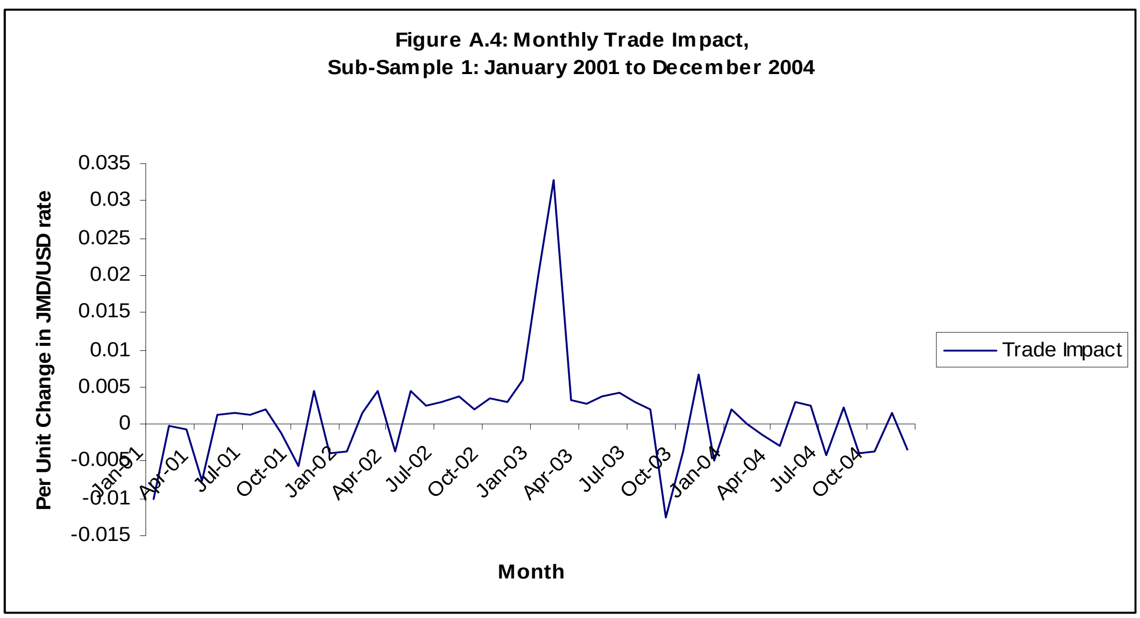
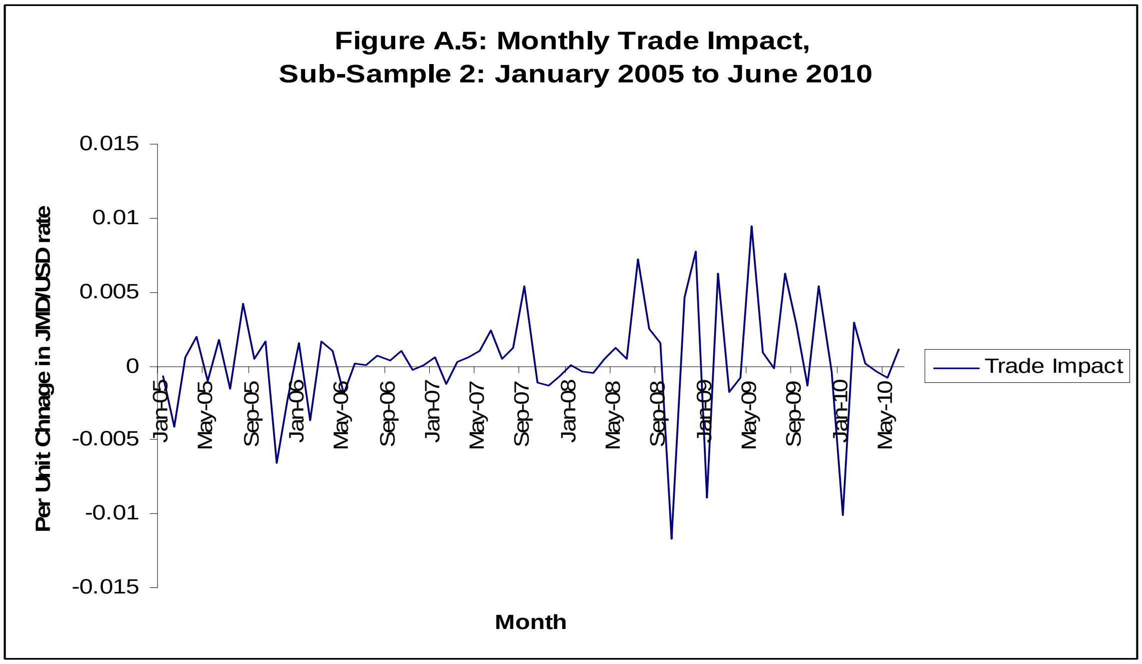


Figure A.4: Monthly Trade Impact,
Sub-Sample 1: January 2001 to December 2004

Source: The Bank of Jamaica



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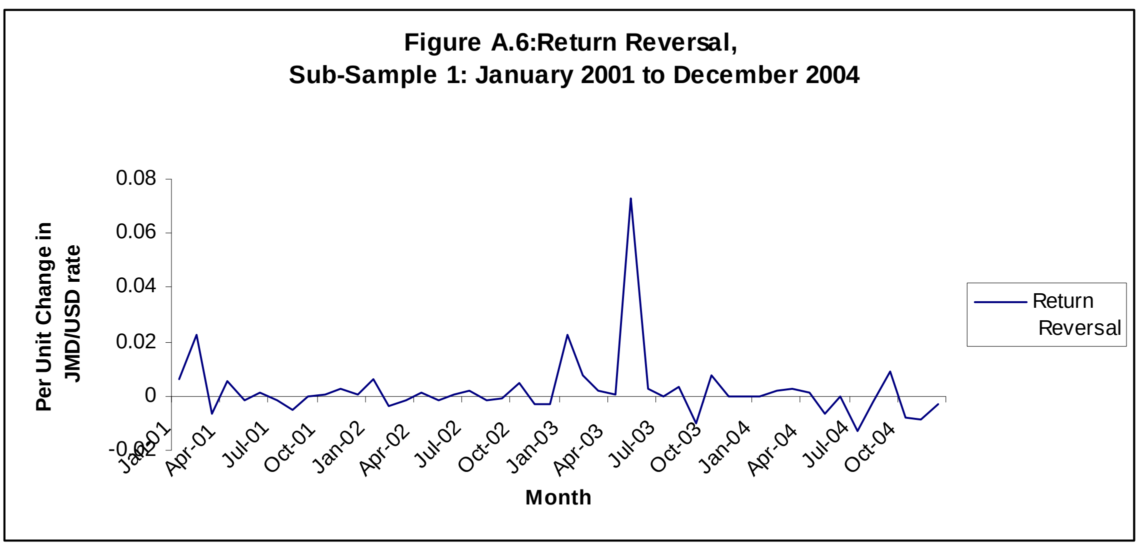

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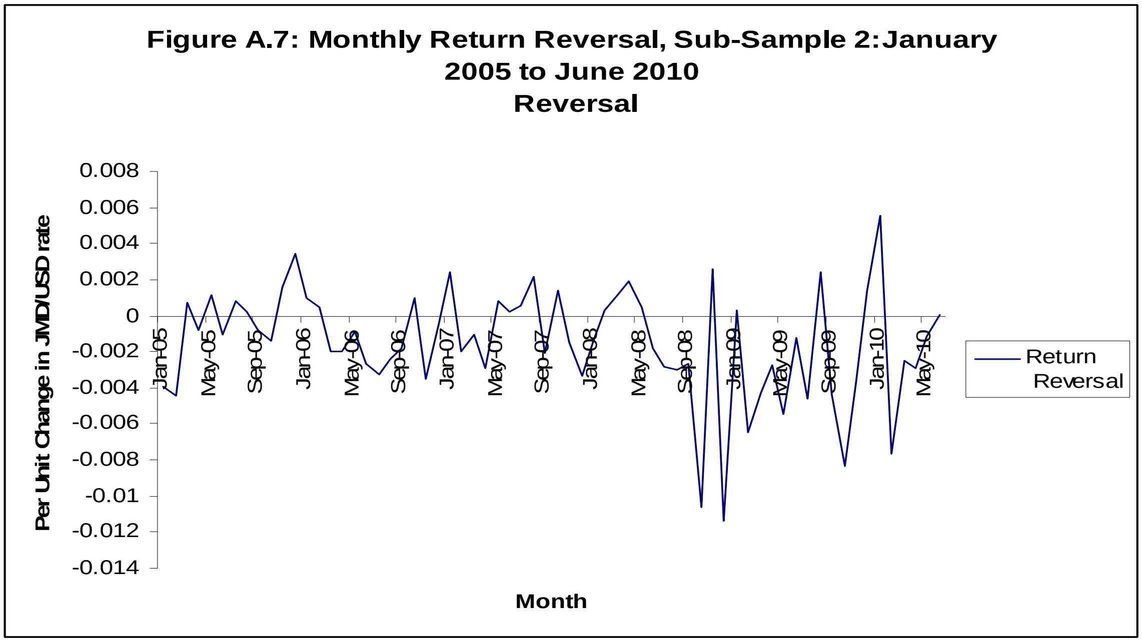

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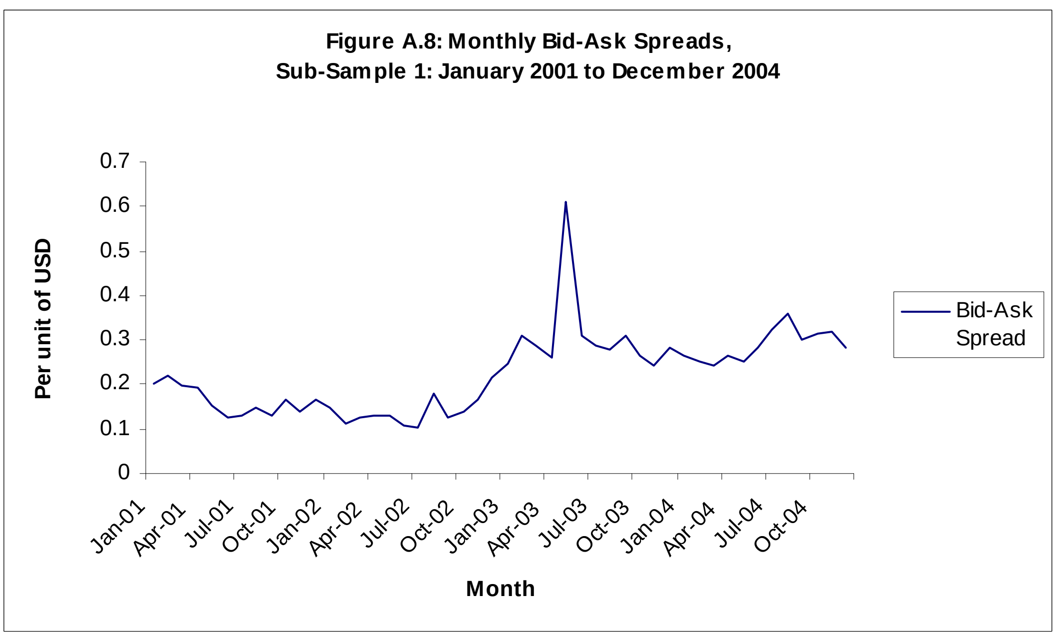

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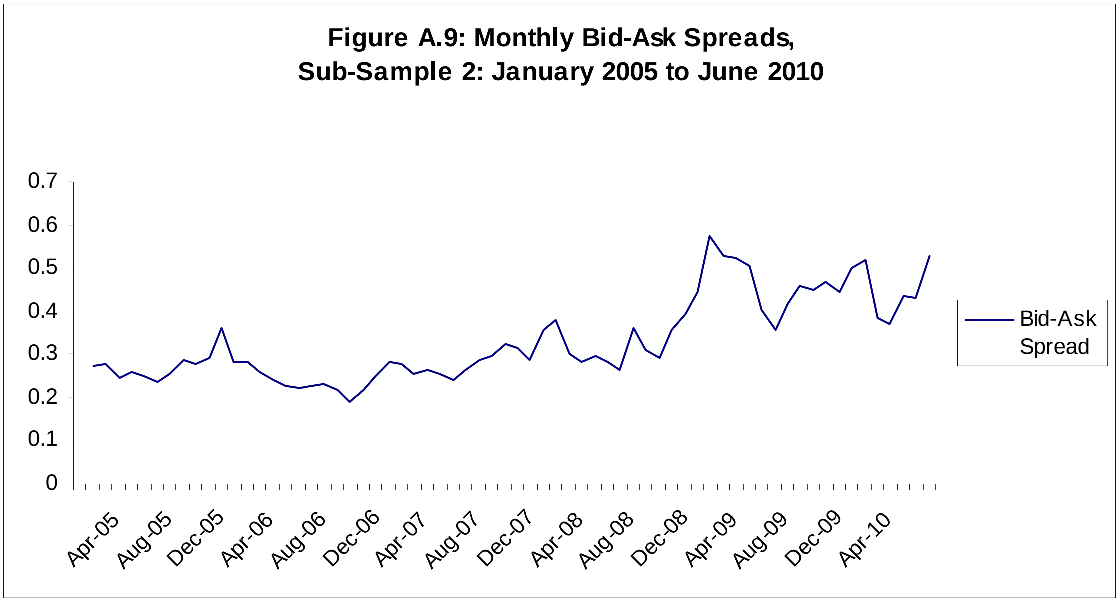

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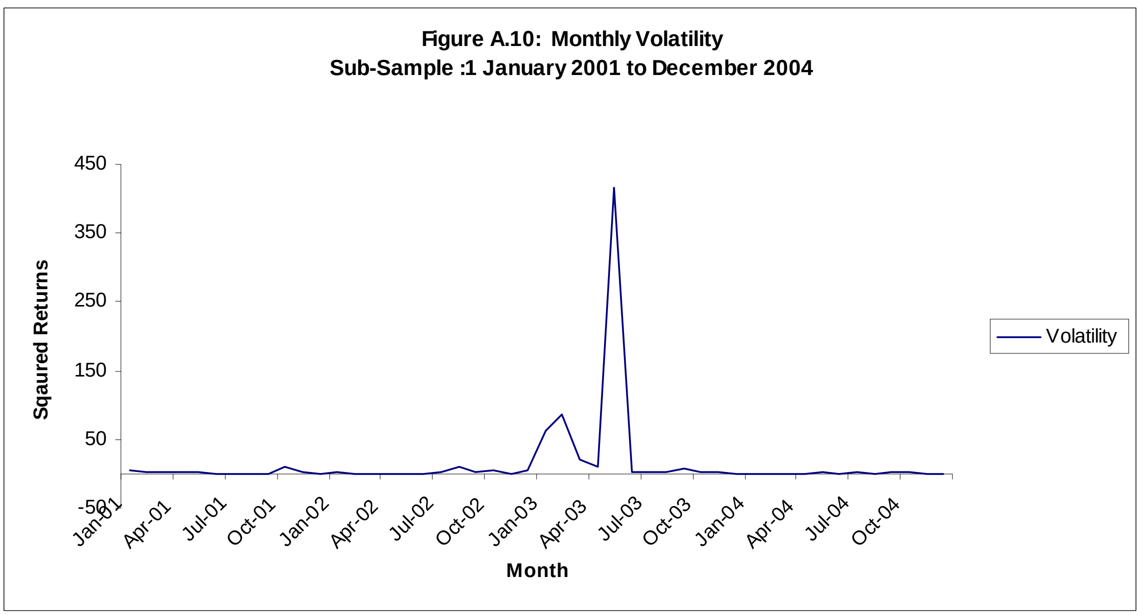

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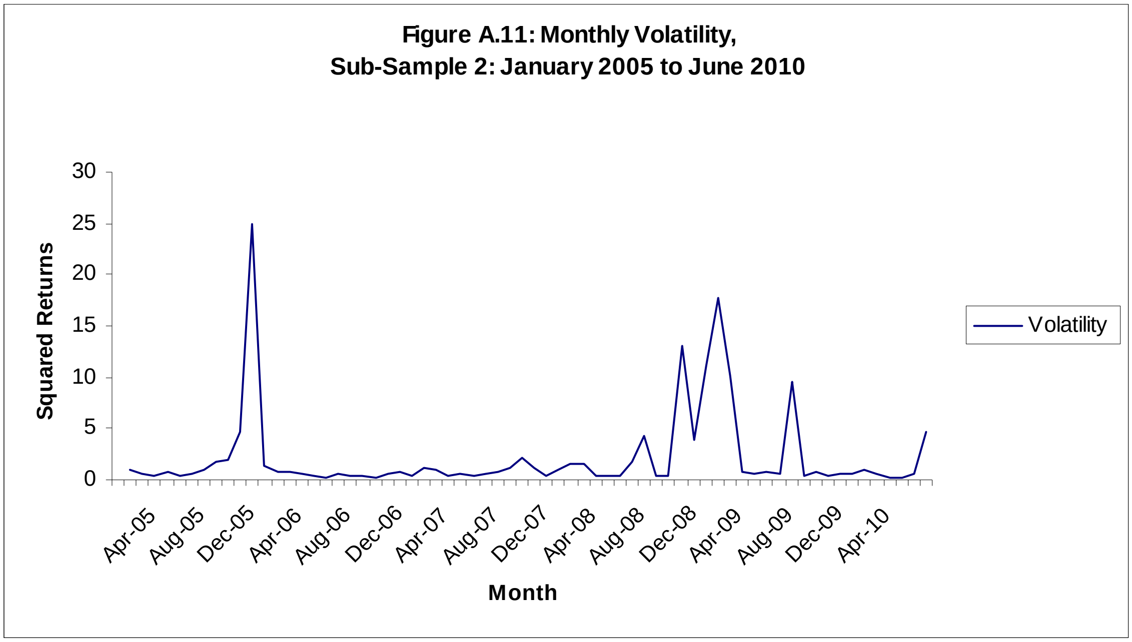

Source: The Bank of Jamaica

Appendix B: Impulse Response Functions and Ordered Probit Graphs

Figure B.1: Impulse response of lagged price changes to a one s.d. shock to itself

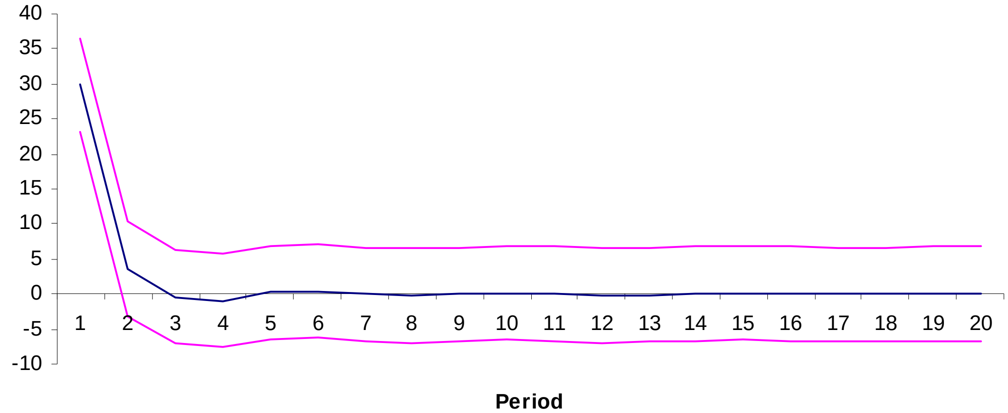

Figure B.2: Impulse response of lagged price changes to a one s.d. shock to lagged volatility

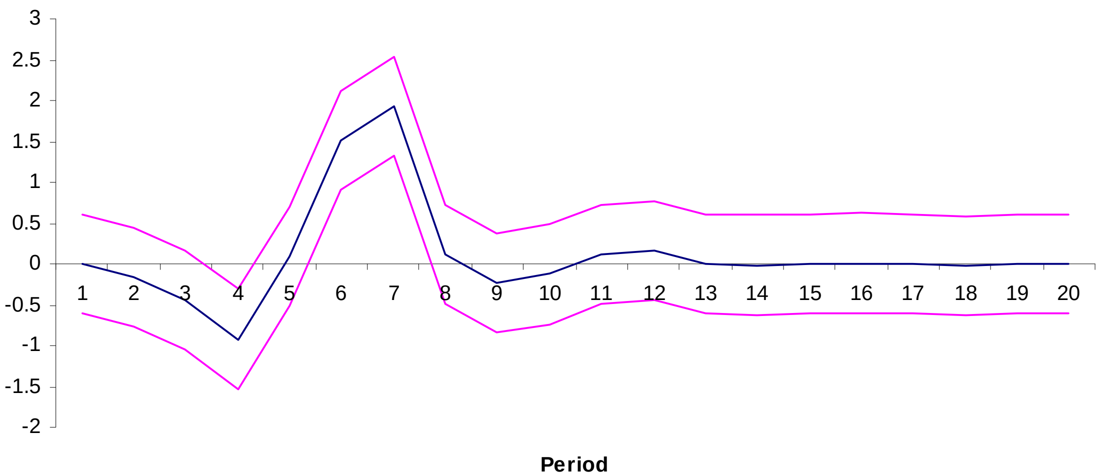

Figure B.3: Impulse response of lagged price change to a one s.d. shock to logged sales volumes

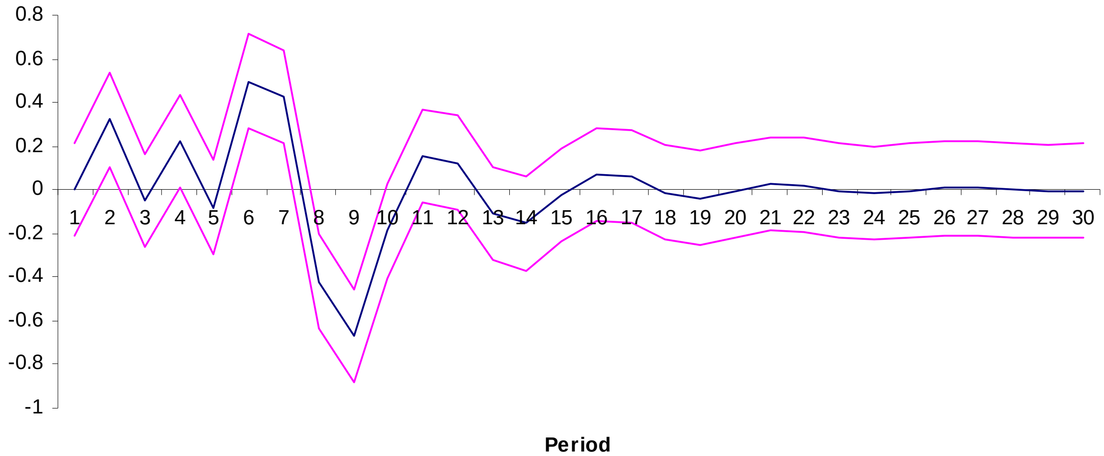

Figure B.4: Impulse response of lagged order flows to a one s.d. shock to logged purchase volumes

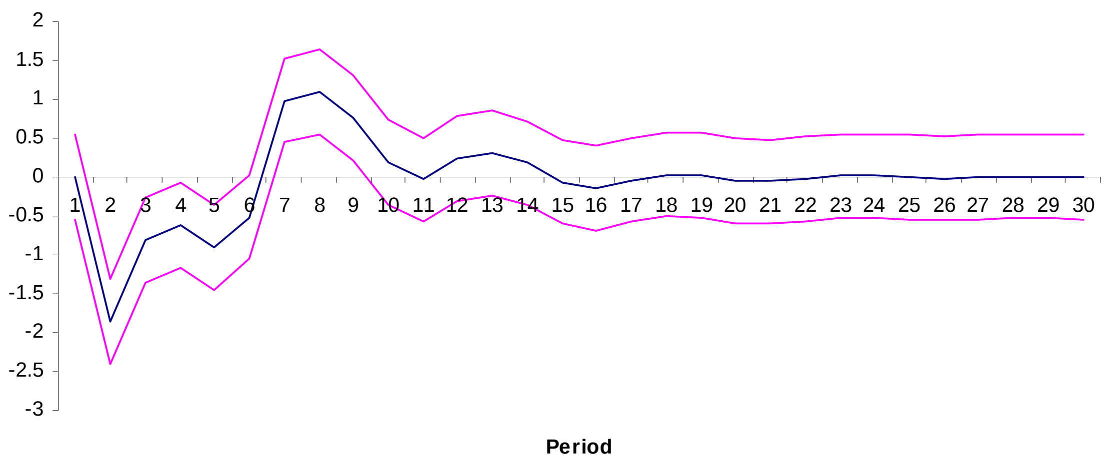

Figure B.5: Intervention, the reaction function, and threshold levels

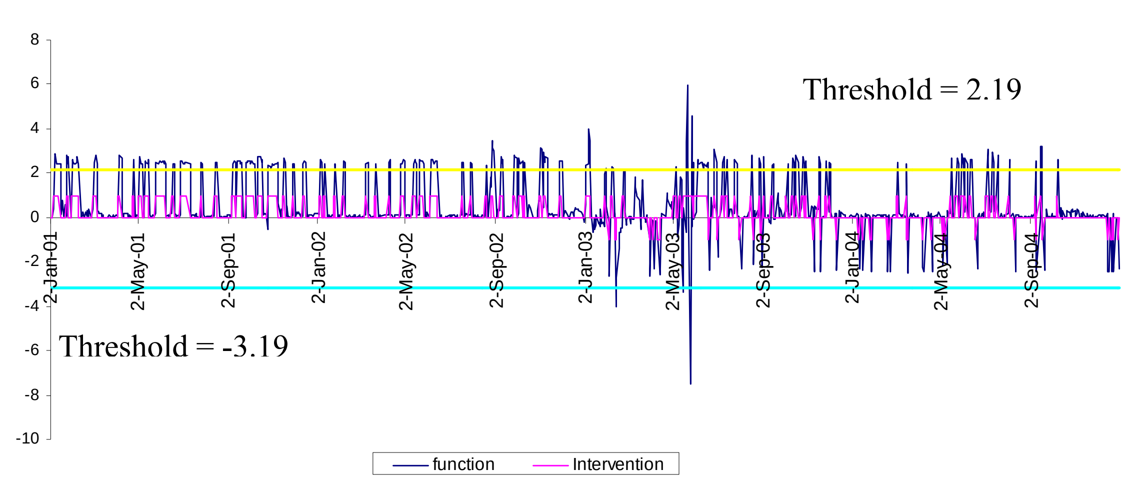

Figure B.6: Intervention, the reaction function, and threshold levels