Exchange Rate Management in Emerging Markets: Intervention via an Electronic Limit Order Book

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Abstract:

This paper describes and analyzes the implementation of a crawling exchange rate band on an electronic trading platform. The placement of limit orders at the central bank's target rate serves as a credible policy statement that may coordinate beliefs of market participants. We find for our sample that intervention increases exchange rate volatility (and spread) for the next minutes but that intervention days show a lower degree of volatility (and spread) than non-intervention days. We also show for intraday data that the price impact of interbank order flow is smaller on intervention days than on non-intervention days. These stabilizing effects, however, rely on the conditions of large currency reserves and the existence of capital controls; an electronic market seems to support this goal.

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I. INTRODUCTION

The bulk of central bank intervention activity nowadays occurs in emerging markets which also play an increasingly important role in current global imbalances. Moreover, foreign exchange (FX) markets have changed their organizational structure to increasingly move to electronic markets and this structural change is taking place in emerging markets, too. This study is the first to analyze the workings of an emerging market's central bank intervention aimed at targeting exchange rates via electronic markets by way of a case study relying on unusually detailed information.

The rise of emerging economies is not yet adequately reflected in the literature on exchange rate management. There is a wealth of studies on foreign exchange interventions but almost all of them refer to industrialized economies and most of them deal with the few main floating exchange rates.[1] Considering the changing institutional features of the FX market, it is worthwhile considering how a central bank could use an electronic trading venue to manage exchange rates. It is also important to note that in recent years, exchange rate management in general and interventions in particular occur mostly in emerging market economies. The share of all reserves held by emerging countries has increased from about 35% to 75% between 1988 and 2007 (Figure 1). Second, effective exchange rate arrangements in the form of crawling pegs or bands

[1] Among the several surveys, Sarno and Taylor (2001), Edison (1993), Almekinders (1995) and Neely (2005) cover the key issues.

dominate floating exchange rates by far, according to Reinhart and Rogoff (2004), and have further gained importance over the last two decades (see Figure 2). Third, much foreign exchange trading has migrated to electronic markets, a technological evolution that applies to emerging markets as well. Therefore, our case study on interventions in an electronically traded emerging market currency seems to address an increasingly important but up to now neglected field of real world exchange rate management.

We report and analyze a unique type of foreign exchange (FX) market intervention by the Russian Central Bank which occurred by placing limit orders on an electronic limit order book to set an upper bound on the rouble price of a dollar (USDRUR). This could be a credible statement of a crawling band that signals a firm commitment of the Bank to spend or accumulate reserves as needed to keep the exchange rate within the band.[2] Indeed, the Russian exchange rate arrangement is classified as a "de facto crawling band" and thus belongs to the important broader category of "limited flexibility" as shown in Figure 2 (see Reinhart and Rogoff, 2004).[3]

The unusually detailed information about the complete order book allows studying intervention effects in an almost "ideal" microstructure setting: we analyze about 2,700 central bank transactions within a total sample of more than 56,000 orders, among them about 30,000 transactions. This data has three distinct advantages: first, it provides knowledge of the exact time of central bank activity which the prior literature

[2] We do not use the term "target zone" here as the formal assumptions of the Krugman (1991) model, in particular no capital controls, are not satisfied.
[3] Among the 31 countries in the "de facto crawling band that is narrower than or equal to +/-2%" category are further transformation economies (e.g. Czech Republic, Lithuania), middle-income African economies (e.g. Algeria, Kenya), a few South-American economies (e.g. Argentina) and emerging Asian economies (e.g. India, Malayisa, Philippines).

has usually inferred from news reports or actual price movements.[4] Thus we can analyze precisely the effects of intervention in terms of the impact of central bank decisions to intervene and the consequent exchange rate effects of purchases or sales of currency.[5] Second, the analysis undertaken in our paper is unique in that we study what could be called "automated intervention" in that the central bank determines a desired band for the exchange rate and then places very large limit orders to keep the exchange rate inside this band. Third, the data allows analyzing order flows which is quite new to the intervention literature.[6]

We find that intervention increases exchange rate volatility (and spread) for the next few minutes but that intervention days show a lower degree of volatility (and spread) than non-intervention days. We also show for intraday data that the price impact of interbank order flow is smaller on intervention days than on non-intervention days. Finally, we reveal that informed banks take different positions than uninformed banks as they tend to trade against the central bank – which reflects a rational stance. Despite this position taking, the targeted exchange rate band holds and volatility, spread and price impact go down. Overall, the intervention band seems to realize stabilizing effects. The

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[4] Exceptions to this are the Swiss National Bank, which has made its data public, see Fischer and Zurlinden (1999), Payne and Vitale (2003), and Pasquariello (2007). Fischer (2006) shows that Reuters news reports of Swiss intervention are often erroneous and bring into question the accuracy of such news for timing Swiss interventions. Data sets from Denmark (Fatum and Pedersen, 2007)and Canada (Beattie and Fillion, 1999, Fatum and King, 2005) have been studied, but are not available to the public.

[5] Starting with Dominguez and Frankel (1993) more recent studies find an impact of intervention, including Humpage (1999) and Dominguez (2003) for the US, Ito (2002, 2007) for Japan, Fatum and Hutchison (2003) for Germany (and the US), Kearns and Rigobon (2005) for Australia and Disyatat and Galati (2007) for the Czech Republic. Also communication can be effective (Fratzscher, 2006) or even falsely rumored interventions (Dominguez and Panthaki, 2007).

[6] To our knowledge there are two other studies analyzing interventions in an order flow approach: Scalia (2008) has to estimate intervention timing and thus aggregates data to hourly frequency, Girardin and Lyons (2007) use customer order flow of a large bank on a daily frequency.

success of such a regime for an emerging market currency is likely to depend on the conditions of large currency reserves and the existence of capital controls—conditions which were met for the Russian case under consideration. In 2002, capital controls in Russia were quite strict. The rigid controls in existence were imposed after the 1998 financial crisis. For instance, business firms had to apply on a case-by-case basis for permission prior to international transfers of capital. Exporters were required to sell 50 percent of their foreign currency proceeds to the central bank. Following the 1998 crisis, firms had a strong preference to hold convertible, reserve currencies like the U.S. dollar or euro, so the currency surrender requirement was viewed as essential to provide liquidity to the domestic foreign exchange market. Foreigners traded the rouble in the offshore non-deliverable forward (NDF) market and could not participate in the onshore market. In 2007, the rouble moved to deliverable status but foreign entities still preferred to trade offshore in many cases due to credit and political concerns. To this day, there is an active NDF market for the rouble.

The paper is organized as follows. In the next section the institutional details of the electronic crossing network will be presented along with a detailed overview of the data available for analysis. Then in Section III, an empirical examination of the limit orders placed by the central bank is undertaken with a focus on its effect on volatility, spread, price impact of order flow and order choice. Section IV discusses implications for the central bank and, finally, Section V offers a summary and conclusions.

II. INSTITUTIONAL DETAILS

II.A. The SELT System

Local interbank trading in the rouble occurs on an electronic limit order market at the MICEX in Moscow and, at the time of interest to this study, March 2002, this market determined the official exchange rate of the USDRUR. This country-wide trading at the MICEX is called the “unified trading session” or UTS. The structure is that of a multiple dealer market without designated market makers. While an interbank market, it is expected that much of the trading reflects customer orders received by the participating banks. During the period analyzed, the UTS took place for one hour a day from 10:30-11:30 Moscow time and the only instrument traded was the USDRUR spot rate.[7]

MICEX FX trading occurs on the SELT electronic system that is similar to the electronic brokerage systems of Reuters or EBS.[8] Like EBS or Reuters, participants on SELT just see the top of the book or the best bid and ask prices with associated order size.

Foreign exchange trading within Russia appears to have a local information component.[9] Banks in the financial centers of Moscow and St. Petersburg are more likely to see the customer order flow of the large Russian corporate clients than banks in other cities. The banks on the periphery are also less likely to be as well informed on economic policy developments as the banks in the financial centers. Menkhoff and Schmeling (2008) show that there is more likely to be a permanent price impact of trades originated by Moscow and St. Petersburg banks than banks on the periphery. This is

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[7] Trading was later extended to a four hour session and forward contracts.

[8] A marginal difference for SELT is that only limit orders, specifying price and quantity desired, or cancellations may be submitted. Unlike Reuters or EBS, there are no market orders specifying desired quantity at the best price in the order book. To receive immediate execution, an order must be submitted that crosses the best price in the order book. Such marketable or crossing limit orders are the equivalent of market orders on the SELT.

[9] See Menkhoff and Schmeling (2008).

consistent with the trades from the financial centers reflecting private information compared to the transitory price impact associated with the trades originated by other banks. Following these earlier findings, we will structure some of our empirical analysis to take account of this institutional feature of the Russian market.

Participants on the system see the best bid and offer price plus respective quantities. They also see the cumulative buy and sell volumes for the current trading session and the last transaction quantity and price. Trades occur anonymously and then post-trade counterparty identities are revealed. The fact that the central bank learns the identities of private banks that trade at its limit order may serve as a form of central bank monitoring that helps to enforce the desired target zone with a minimum of reserve loss.

It is likely that using an electronic limit order book as a vehicle for maintaining a target zone is effective only in a case where that crossing network accounts for a very significant part of the overall market. In the case of Russia, this was made possible by the controls on foreign exchange trading. Foreigners traded roubles in an offshore market in the form of non-deliverable forward contracts. So the domestic market was segmented from foreign participation and this allowed the central bank to effectively target the exchange rate with limit orders on the MICEX.[10] Such a mechanism is unlikely to be of much use to a country with a convertible currency and open financial markets given the current structure of the foreign exchange market. For instance, electronic trading in the major developed currencies is split across several different platforms and there is no one crossing network that has a dominant portion of overall liquidity. Over time, if liquidity

[10] We thus observe and analyze the trading dynamics of the domestic market. Within domestic markets, the UTS provides much higher liquidity than regional bourses which are only open to banks from the respective regions. Moreover, the central bank determines via its interventions the official exchange rate at the UTS which is then binding to others. Thus the UTS is the core market to exchange information among domestic players.

concentrates on one platform and electronic trading comes to dominate the large and active over-the-counter market, it may be possible to think of managing a target zone via an electronic limit order market for the major currencies. But for emerging market currencies with segmented domestic foreign exchange markets, the existence of an electronic market that pools liquidity for domestic trading may serve as a useful vehicle for operating a target zone and may thus provide an efficient alternative to more conventional interventions in the OTC market.

II.B. Data

We study a unique data set on the Russian interdealer FX market for USDRUR over a period in March 2002 during which the central bank used the market for intervention purposes. There were 722 traders participating in the market at this time. While participants only see the best bid and ask orders in real time, we have anonymous data on the entire order book, or every submitted and cancelled order and trade that occurred on the system during this period. The data are stamped to the second and we know the initiator of each transaction, although true identities are unknown to us. The data also indicate the regional location of the bank submitting the order.

The data cover the period from March 1 to March 22, 2002. This includes days with major FX market intervention by the central bank and provides a unique view of a central bank using an electronic limit order book to set an exchange rate bound. Table 1 provides descriptive statistics for each day in the sample. At the bottom of the table, summary statistics are given for March 1 to 7, the days of central bank intervention. On these days, the central bank's limit price served as an upper bound on the price in the market. Note that these were the days of heaviest trading volume that month, with average trade size of $91,024 on those 5 days compared to $49,401 on the other days. The central bank's ask price was the effective limit in the market and there were many more trades that occurred at the central bank's ask price (2,584) than bid price (109) over those days. It is notable that the maximum price in the market on March 4-7 was 30.9950. The central bank's ask price bounded the exchange rate from above as the market actively consumed the central bank's liquidity.

Table 2 summarizes the order and trade activity of the central bank and the private banks. This yields a picture of a market where the private bank trades with the central bank tend to be large versus a relatively small size of the private interbank trades among themselves.

II.C. The Central Bank's Intervention Threshold

Intervention via the limit order book occurs by the central bank placing a large limit order at the beginning of a trading session and then meeting all orders that cross that price. While limit orders could bound the exchange rate on both sides of the market, the Bank of Russia faced depreciation pressures which made their ask limit orders much more important as seen in Figure 3. Submitting a very large ask limit order at the start of each day allowed the central bank to control the daily rate of depreciation in a kind of crawling peg arrangement.

The effect of such an arrangement is clearly seen in a plot of the limit order price and counterparty activity for a day when the central bank's limit price becomes one side of the inside spread in the market. The upper panel of Figure 4 illustrates the central bank's limit orders and the market price for March 1-7. On March 1, the central bank set a narrow range for the rouble with a bid price of 30.9400 and an ask price of 30.9450, which rises to 30.9500 late in the session. It is seen that many trades occurred at both sides of the central bank's orders. Then from March 4 onwards, the ask price limit is raised to 30.9950 and the market consistently trades at that price over the day. The middle panel of Figure 4 shows the central bank's limit order volume at the ask price. During these days the market traded very often at the central bank's ask price and the quantity on offer fell steadily during these automated intervention activities.

III. EFFECTS OF CENTRAL BANK LIMIT ORDERS

III.A. The Intervention Effect on Volatility and Spread

The microstructure literature on foreign exchange interventions has not produced fully conclusive results about the intervention effect on exchange rate volatility. Whereas interventions are tentatively conducted in order to reduce volatility (see Neely, 2008), their success has been questioned and high frequency analyses show that interventions increase short-term volatility (Dominguez, 2006).

The literature on this subject is limited by appropriate data to overcome the identification problem: Are interventions related to volatility because they aim for stabilizing volatile markets or do they create volatility? At the daily data frequency the relation between interventions and volatility is positive, so intraday data seem helpful in solving the causality issue. Indeed, at high frequency there is not much doubt that interventions are treated as news by the market and lead to a similar reaction, i.e. a short-term volatility increase.[11] At the daily level, however, there is still controversy whether possibly the exchange rate regime may play a role. The target zone model predicts that a credible commitment should reduce volatility: it seems plausible that a central bank fixing – in our case in particular – the ask price reduces risk to a one-sided risk which should lower volatility and spread. There is also evidence from the Canadian experience with a pre-announced non-intervention band which seemed to lead to somewhat lower volatility due to interventions (Beattie and Fillion, 1999).

We use our tick-by-tick data to construct a time series sampled at a 30 second frequency to eliminate microstructure noise.[12] With this data at hand we examine determinants of volatility, measured by the standard deviation of midquotes within a 30 second interval.[13] The approach aims for integrating the intraday and daily view by considering the effect of lagged interventions, i.e. during the last few minutes, and also considering a dummy variable for intervention days. The equation we estimate via OLS with Newey-West HAC standard errors is

$$\hat{\sigma}_{t+1} = \alpha + \sum_{j=1}^{4} \beta_j \cdot share_{t+1-j} + \lambda \cdot CBday_{t+1} + \boldsymbol{\Theta}_t \boldsymbol{\gamma} + \varepsilon_{t+1} \tag{1}$$

where $\hat{\sigma}_t$ is the midquote return standard deviation (i.e. the standard deviation computed for successive 30 seconds intervals), $share_t$ is the share of total trading volume in a 30 second time interval transacted with the central bank as counterparty, $CBday_t$ is a dummy

[11] This has been nicely demonstrated by D'Souza (2002) who compares the effect of interventions versus replenishment operations of the central bank on volatility: interventions increase volatility, non-interventions do not.

[12] Investigating data aggregated over fixed calendar time is quite common, see e.g. Evans and Lyons (2002, 2002a). Results are robust when sampling at a different frequency, e.g. one minute (see Payne (2003) for similar findings).

[13] Using the absolute return over a 30 second interval or the sum of squared returns yields qualitatively the same results.

indicating days with central bank activity[14], and Θ_t is a vector of (lagged) control variables. Depending on the specification employed, Θ_t includes lagged volatility, lagged bid-ask spreads (i.e. the mean bid-ask spread over a 30 seconds interval), lagged trading volume and deterministic time patterns (the time variable is just the minute of the trading session). Note also, that here and in all further econometric estimation exercises, we eliminate overnight observations. For example, in the regression above, the first four 30 second intervals are eliminated from the sample and show up as lagged values in the above regression only.

The left panel of Table 3 contains estimation results for different specifications of Θ_t and shows that both volatility effects discussed above are significant: first, volatility increases directly after interventions and keeps the significantly increased level for about one or two minutes, i.e. the β_j's are significant. Second, volatility is significantly lower during intervention days as indicated by the highly significant estimate for λ.[15] As controls in the full specification (iii) we use lagged volatility, then lagged spread and transaction volume to consider possible delayed effects from earlier events and finally two time variables to consider a possible volatility pattern during the one hour opening time. However, whether controls or subsets of these controls are used or not, results remain stable. Therefore, the effect is unlikely to result from higher trading volume due to central bank trading since trading volume is included as a control in the regression and

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[14] Since all intervention days have trades with the central bank right at the beginning of the day (see e.g. Figure 2), the fact that the central bank intervenes on a given day is visible to the market and, thus, public information. Therefore, we use the CBday dummy in its form described above. However, using a dummy variable that indicates lagged intervention days, i.e. interventions at the day before, does not change the qualitative conclusions.

[15] These effects also hold when we test them in isolation and without any controls.

since trading volume and the share of central bank activity (*share*) is not significantly correlated on intervention days.[16]

For reason of robustness, we re-estimate the above specification with a different volatility proxy, namely the high-low range measured over the intervals of 30 seconds. Results are reported in the right panel of Table 3 and confirm our findings for a negative overall effect of interventions on volatility and for a short-run positive effect. The only notable difference is the significance of the lagged share variable. The short-run effects of central bank interventions seem to die out somewhat more quickly compared to using standard deviations as volatility proxy. We also provide estimates of GARCH(1,1) models to further strengthen the robustness of this central result. It can be seen from Appendix 1 that the main results regarding the effects of intervention are unchanged when using this specification to model conditional spot rate volatility.

We conclude that the Russian exchange rate band policy during the sample period has two effects on volatility, which have – to the best of our knowledge – not been analyzed in a single approach before: automated intervention reduces volatility at the daily level and increases volatility in the minutes following a trade at the central bank's ask price.

Next we analyze the effect of intervention on bid-ask spreads. There are hardly any papers examining this relation as appropriate data are generally unavailable. The studies of Chari (2007) and Pasquariello (2007) rely on quotes which are tentatively wider than effective spreads and do not necessarily reflect market conditions as precisely. Both studies find that spread increases after interventions, indicating that a

[16] As can be seen in Table 1, daily trading volume and CB activity is correlated. However, in the intraday analysis conducted here (intervals of 30 seconds), we do not find a high correlation of volume and the *share* variable.

volatility reducing effect may be counter balanced by higher transaction costs for customers (see Naranjo and Nimalendran, 2000, for daily data). Thus, we test this by using an equivalent specification as we did above for volatility:

$$\left(mean\,spread\right)_{t+1} = \alpha + \sum_{j=1}^{3} \beta_j \cdot share_{t+1-j} + \lambda \cdot CBday_{t+1} + \boldsymbol{\Theta}_t \boldsymbol{\gamma} + \varepsilon_{t+1} \qquad (2)$$

where (mean spread)$_t$ is the average bid-ask spread over a 30 second interval and all other variable definitions remain unchanged. Note, that we use only three lags of the *share* variables since further lags are generally insignificant and also increase the AIC. Again, one might use a censored regression model. However, the results do not change when doing so.

Results are shown in Table 4 and we find a negative significant sign at the daily level and a very short-lived spread increase after interventions. Obviously, spread effects go in the same direction as volatility effects in our sample.

The increase in spreads directly following interventions seems to be – at least partly – driven by lower liquidity. We find some (unreported) evidence that limit order submission decreases subsequently to reaching the central bank’s quote which might explain the temporary surge in spreads. However, the effect on spreads is short-lived and is clearly outweighed by the overall reduction in spreads on central bank intervention days.

Overall, in the case studied here intervention policy seems to contribute towards stable markets without noteworthy costs for the public.

III.B. The Exchange Rate Band Effect on the Price Impact of Order Flow

We extend the analysis of an automated target zone effect on trading activity by considering high frequency order flow. The theoretical expectation of the price effects of order flow is motivated by Girardin and Lyons (2007). Following the intuition of Krugman (1991), a credible exchange rate band should dampen the price effect of order flow as the limit of the band is approached. Taking into account that order flow transports information (Lyons, 2001), days when the central bank's limit is reached should be characterized by a lower price impact of order flow, i.e. that the exchange rate is less responsive to the arrival of information. Girardin and Lyons (2007) do not find clear evidence for such an effect for daily end user order flow of Citibank in the Yen/US dollar market.

We run price impact regressions of order flow on returns, as in Evans and Lyons (2002), i.e. we estimate via OLS a regression of the following form, again on the basis of 30 second intervals:

$$\Delta m_{t+1} = \beta_0 + \beta_1 OF_{t+1} + \beta_2 OF_{t+1} CBday_{t+1} + \beta_3 OF_{t+1} CBday_{t+1} Dist_{t+1} + \gamma \Theta_t + \varepsilon_{t+1} \quad (3)$$

where Δm_{t+1} is the midquote return over the chosen interval, OF_{t+1} is the order flow indicator[17] and *CBday* is a dummy that equals one on intervention days.[18] *Dist* denotes the average distance to the upper limit of the Central Bank's target zone, and, again, Θ_t

[17] The order flow indicator equals one if a trade is buyer initiated and minus one otherwise. All order flow indicators in a 30 second interval are aggregated to yield the aggregate order flow indicator for the respective interval which is used here.

[18] One may think of this specification as a varying parameter model where

$$\Delta m_{t+1} = \beta_0 + \lambda_t OF_{t+1}$$

$$\lambda_t = \beta_1 + \beta_2 CBday_{t+1} + \beta_3 CBday_{t+1} Dist_{t+1}$$

$$\Delta m_{t+1} = \beta_0 + \beta_1 OF_{t+1} + \beta_2 OF_{t+1} CBday_{t+1} + \beta_3 OF_{t+1} CBday_{t+1} Dist_{t+1}$$

contains control variables, namely lagged midquote returns and order flows. T-statistics are based on Newey-West HAC standard errors.

For this specification we again rely on the 30 seconds frequency, and we exclude all trades at the central bank limit because the impact is in these cases necessarily zero. Results presented in the left panel of Table 5 show that the relation between order flow and returns is highly positive and of the same order as in other studies.[19] The interaction term of order flow with the central bank dummy is significantly negative. This indicates that price impact is dampened due to the intervention band. A Wald test of the restriction $\beta_1+\beta_2=0$, which would indicate that the price impact completely vanishes on intervention days, cannot be rejected at any reasonable level of significance. Furthermore, the interaction term with the distance variable *Dist* tends to be positive and is marginally significant. The estimated coefficient in specification (v) of Table 5 indicates that a one standard deviation increase in the distance variable increases the price impact of order flow by slightly less than 20%. Therefore, trades occurring farther away from the Central Bank's crawling band have a tentatively higher price impact which seems to be intuitively related to the "honeymoon effect" of Krugman's (1991) target zone model as suggested by Girardin and Lyons (2007).

We complement the above analysis by running the same sort of regression with a measure of unexpected order flow following Pasquariello and Vega (2007). While the above regressions directly use order flow as a determinant of midquote returns, attention

[19] Evans and Lyons (2002a) find that the order flow coefficient is 0.6 basis points per $10 million for DEM/USD and goes up for smaller markets, such as 2.4 for the Australian dollar, while Scalia (2008) finds an even higher value of 7.6 for the Czech koruna. The order flow coefficients in Table 4 are for order flow indicators and have to be multiplied by a factor of 20 to obtain the impact per $10 million. Table 4 suggests that the impact on non-intervention days is about 0.123, so that we have an average impact of $0.123 \times 20 \approx 2.5$ basis points.

also focuses on the effect of the unexpected part of order flow, i.e. order flow *shocks* hitting the market. To compute this measure of unexpected order flow, we estimate logit models with the order flow indicator as dependent variable and lagged order flows and midquote returns as right-hand side variables. The regression uses tick-by-tick data in event time. The residuals from this logit regression are free of predictable components in the raw order flow indicator and should thus provide a better measure of information shocks than raw order flow itself. For the empirical analysis we aggregate the generalized residuals from these regressions to the 30 seconds frequency as above and re-run regression (3) with this measure of unexpected order flow.[20]

Results are given in the right panel of Table 5 (specifications (vi) – (viii)). Eliminating predictable components from the raw order flow measure does not change our general results. This conclusion is similar to Pasquariello and Vega (2007) and it shows that our results are not driven by simple endogeneity problems caused by feedback trading where causality (partly) runs from midquote changes to order flow.

Finally, we can exercise another robustness test due to the high frequency data available which is able to discriminate between mechanistic transitory liquidity effects of order flow and its permanent information transmission. We estimate price impacts according to the Hasbrouck (1991) metric, i.e. as the cumulative response of midquote returns to order flow shocks in a SVAR-model. More specifically, we estimate a SVAR with midquote returns and market order flow as endogenous variables:

$$Ay_{t+1} = \Gamma(L)y_t + Bv_{t+1} \quad with\, Var[v_{t+1}] = I_2 \tag{4}$$

[20] Estimation of the logit model in event time is done separately for each day. As usual, we eliminate overnight observations and the lag length for past order flow and midquote returns is determined separately for each day by minimizing the AIC. The average lag length across days is one for lagged order flow and two for past midquote returns.

where $y = [\Delta m_{t+1} \;\; OF_{t+1}]^T$,

$$A = \begin{pmatrix} 1 & -\alpha_1 \\ 0 & 1 \end{pmatrix} \text{ and } B = \begin{pmatrix} \beta_r & 0 \\ 0 & \beta_x \end{pmatrix} \tag{5}$$

so that the SVAR is just-identified and causality runs from order flow to midquote returns via α_1. $\Gamma(L)$ is a matrix polynomial in the lag operator and the number of lags is chosen by the AIC for each subset of observations employed in the estimation detailed below. Permanent price impacts are computed by calculating the long-run cumulative response of midquote returns to order flow shocks (see e.g. Evans and Lyons, 2002a, or Payne, 2003 for applications of this procedure to FX spot rates).

The first row in Table 6 shows permanent price impacts of order flow on returns for intervention days (left column) and non-intervention days (right column). As can be seen, and corroborating the evidence from the Evans-Lyons-type regressions in Table 5, order flow has a much larger price impact on non-intervention days than on intervention days, consistent with our expectations.[21]

In order to further examine whether the degree of price impact robustly depends on the fact of interventions or not, we compare the average price impact on intervention days with non-intervention days under various market conditions. Thus we condition the price impact analyses on variables that reflect market conditions typically found to be important in microstructure analysis. We use transacted volume as a proxy for market activity, midquote return volatility as a rough measure of information arrival and spreads to reflect the degree of asymmetric information in the market.[22] We then split the sample

[21] The price impact of 0.721 for "all trades" on intervention days in Table 5 roughly translates into a midquote movement of 2.4 pips. This is small compared to the permanent impact on non-intervention days which is about 4.9 pips.

[22] These variables are also detrended to eliminate typical intraday patterns and thus to rule out the indirect influence of time. Therefore, we project each of the sorting variables on 60 time dummies representing the minute of the trading session. We then use the predicted values of this

into two subsamples according to whether a sorting variable is below or above the sample median and the permanent price impact of order flow is calculated for intervention days and non-intervention days. Results of this procedure are given in the remaining rows of Table 6.

Results show marked variation in price impacts under different market conditions. Price impacts tend to be higher in times of more market activity, higher volatility and higher spreads, so that times of higher market activity seem to indicate more information processing. Most interesting for our analysis is, however, that price impacts differ in an economically significant way between intervention and non-intervention days. Price impacts are much higher on non-intervention days in all regimes except the high volatility regime where the price impact increases only slightly. This again corroborates our finding that interventions dampen the impact of information arrival on spot rate movements.

III.C. Order Choice of (Un)Informed Traders during Intervention Days

We know from the earlier descriptive parts of this paper that there seem to be participants trading “against” the intervention band as can be seen from the loss of reserves in the bottom panel of Figure 4. At first sight this may be unexpected, given the credibility of the intervention band. A plausible interpretation of this fact may be, however, that a later depreciation of the rouble is expected due to some pressure from fundamentals and that either informed banks or informed customers of these banks trade

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regression as the intraday pattern and divide the actual observations by the predicted value of the corresponding interval.

on their anticipation.[23] In the following, we therefore seek to answer the following question: who is trading against the central bank and how do they do it?

There is indeed Reuters headline news supporting the view of a fundamental pressure towards rouble depreciation. On March 4 for example, there is Reuters news in which a market participant reports that "there are roubles available on the market. […] and banks used the opportunity to take long dollar positions expecting the rouble to go further down". On another case, on March 6 a market participant is quoted with the following statement: "it is the usual story of past few sessions: banks build up speculative positions (against the rouble) early, then the central bank comes out to the unified session offering dollars at 30.9950 and the market obeys, […]".

To explore who might be trading against the central bank's crawling band, we exploit another feature of our data, i.e. its disaggregation of trading banks into more or less informed participants, as discussed in Section II.A. Regarding the analytical framework, we use an order choice approach and analyze who is trading against the band and who is supporting the band. We do this by focusing on the following "distance variable": *Distance* from central bank's ask is the difference between the actual ask price of the central bank and the last transaction price (in pips). This variable is used to test whether the likelihood of trading against the central bank (the likelihood is high when the distance is low) influences the behavior of traders. If the heavy buying at the central bank's ask is noise trading, then the share of buy orders should be largely independent of the distance from the intervention price. Moreover, there should be no difference between more and less informed traders.

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[23] In the latter case, that is pressure from customer trading, banks have to cover their open positions.

There may of course be other relevant determinants of the trading direction and the empirical order choice literature indeed suggests that one should model trading decisions as a function of momentum, herding, ask volume, bid volume and time, in order to capture time-varying dynamics of market conditions (Hasbrouck and Saar, 2007, Ranaldo, 2004). Thus, we control the decision to buy or sell, i.e. the order choice, by a set of determinants which are standard in the respective literature:

Momentum, which is measured as the midquote change over the past 30 seconds preceding an order. As in earlier studies we direction-adjust order flow by multiplying it by minus one if the current order is a sell order. This price momentum is intended to capture price pressure which induces adjustments in the order strategy of traders.

Learning, which is measured as cumulative order flow over the past 30 seconds. Similar to the above price momentum, this variable is direction adjusted. We include it to capture the general trading direction. Since traders seem to learn from observed order flow (Lyons, 2001), changing order flow trends might induce different order placement strategies.

Ask volume is the size of the best order on the ask side of the book and thus visible on the trading screen. Similarly, *bid volume* is the size of the best order on the bid side of the book and also visible on the trading screen.

Same side volume is measured as the volume at the bid just prior to a buy order's submission and as the volume at the ask just prior to a sell order's submission, respectively.

Other side volume is measured as the volume at the ask just prior to a buy order's submission and as the volume at the bid just prior to a sell order's submission, respectively. This and the preceding variable are suggested by Parlour's (1998) model of limit order placement. The two volume variables are found to be important empirically e.g. in Griffiths et al. (2000) or Ranaldo (2004).

Time indicates the minute of the trading session (1, …, 60) and is used to capture deterministic time patterns.

We estimate a logit model, where the dependent variable is coded *1* if the market order is a buy and *0* for a sell. The model is estimated separately for two groups: there are trades from the center, i.e. banks from Moscow and St. Petersburg, who are expected to be better informed, and others who are expected to be relatively uninformed. Estimation results are presented in Table 7.[24]

We see that trading behavior of both groups is different. Traders from the center, i.e. Moscow and St. Petersburg, buy more when the price comes closer to the upper intervention level, whereas traders from the periphery behave in a contrary manner.[25] Among the control variables, learning is the only one which has the same significant sign for both groups. The further variables are different as center traders buy with momentum and later in the session. Periphery traders, however, buy more when the ask volume is larger, bid volume smaller and earlier in the session. Overall, the significantly different behavior of better informed center and less informed periphery traders suggests that

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[24] Following the suggestion of a referee, we have also estimated the model without the learning variable. Results are qualitatively unchanged.

[25] As another approach to address this issue, we examine by way of a logit model the order choice between marketable limit orders that receive immediate execution (1) and all other limit orders (0)(see Appendix 1). Again, if not due to heterogeneity in trading motives, there should be no difference between the likelihood of using one of both order types, with respect to price distance from the central bank's ask. However, we find that Center traders are more likely to submit orders for immediate execution when the price is closer to the upper intervention band, i.e. they trade more aggressively when the price comes close to the central bank's limit.

traders' buys at the ask may be no accident but a sort of speculative mini-attack on the target zone.

IV. IMPLICATIONS FOR THE CENTRAL BANK

The posting of limit orders is an effective device for containing exchange rate movements within narrow bounds. Our case study shows that the Bank was successful in stabilizing the market in several respects. However, what are conditions for such a policy to be implemented in general and which role does the electronic market form play?

The ability of maintaining a credible exchange rate band depends upon the central bank posting a quantity that is large relative to the market so that whenever the central bank's quote rises to the top of the order book, the market cannot exhaust the quantity on offer and move the exchange rate outside of the central bank's desired range. In this analysis of the Russian central bank's activity on an electronic crossing network, it is clearly the case that the central bank's limit orders are very large relative to the quantities traded on this market. This conveys the image of a credible crawling exchange rate band.

Credibility of this exchange rate arrangement seems to be supported by strict capital controls which separate the domestic market from international financial markets. This institutional requirement ensures a limited market power of private participants who might trade against the central bank's intentions. As capital controls are widespread in emerging markets, it seems reasonable that similar intervention strategies should work in other emerging markets controlling large currency reserves in relation to the respective currency market volume. Interestingly, the market organization of a modern electronic crossing network is no disadvantage in implementing a credible exchange rate band, as we argue below.

The literature on intervention has often focused on the channel through which intervention changes exchange rates. The typical discretionary central bank intervention is accompanied by sterilization of reserve flows in order to leave the money supply unchanged. Sterilization also seems to occur in Russia during the period we study. Since interest rates and prices are left unchanged, the usual avenues through which exchange rates are changed include the portfolio balance and signaling channels, or coordination of expectations (e.g. Reitz and Taylor, 2008). In the special case where intervention occurs through limit orders on an electronic crossing network, it may be less likely that relative bond supplies are changed so that the portfolio balance channel is not a likely candidate. There is clear signaling of the central bank's desired exchange rate with the posting of a limit order that the market learns must come from the central bank. In addition, such a posted limit order, with a very large quantity associated, serves as a credible mechanism for coordinating the expectations of market participants.

However, when a central bank supports the domestic currency by providing a perfectly elastic supply of dollars at a given exchange rate, reserve losses will be associated with trades that occur. In the case under study, where we know the trade sizes, it is possible for every trader to calculate the (cumulated) reserve losses associated with the intervention activity. The lower panel of Figure 4 depicts the cumulative loss of reserves. The changing slope of this line reflects trade sizes at the central bank's ask price. Over the week as a whole, the central bank sold approximately $338 million dollars for roubles during the electronic trading sessions which equals about one percent of reserves. If reserve losses are estimated to be reaching a threshold that would lead to the central bank's removal of the limit order, one would expect traders to be even more aggressive in trading at the central bank's price. This may be seen as a short-term disadvantage for the central bank but the visibility of interventions and thus changes in reserves will also have a disciplining effect on the intervention policy of a rational central bank. Thus, visibility of reserve losses should incentivize long-term credibility of exchange rate management.

The data indicate that on March 7 there were some large trades late in the session as the loss of reserves increases steeply on this day. It is notable that on the next day, the central bank allowed the official exchange rate to depreciate to 31.1 as seen in Figure 4. Thus, the reserve losses occurring on March 7 may represent a sort of "mini speculative attack". The fact that there was no limit order placed at 30.9950 on March 8, so that the exchange rate was allowed to depreciate, is consistent with the central bank defending its reserves by allowing the depreciation. As the Russian central bank was far away from exhausting its reserves (the losses were only about one percent of total reserves), its decision was deliberate in realizing a crawling peg. We interpret this episode as evidence that even in a regime with capital controls it is costly for the central bank to support its currency against obvious fundamental trends. It is often the case that a central bank's goal is not to achieve a hard peg but to reduce volatility in the exchange rate and moderate the rate of depreciation in line with a crawling peg regime.

Finally, a potential central bank advantage of intervening in the passive form of posting limit orders is that the identity of counterparties is revealed after each trade is completed. This information may be useful in enforcing good behavior on the part of the private banks as they know the central bank can monitor their trades when the central bank is the counterparty. If the central bank exerts moral suasion or other enforcement mechanisms, which may be more effective in emerging compared to industrialized countries, then private banks may regulate their trades at the central bank price to avoid any appearance of an attack on the central bank. This mechanism may be weakened, however, if private banks just intermediate trades for their informed customers who are not necessarily revealed to the central bank.

In summary, the Russian case may demonstrate to emerging economies with large reserves and capital controls a way of implementing a stabilizing crawling exchange rate band. The existence of an electronic currency market may offer advantages in executing such a policy.

V. SUMMARY AND CONCLUSIONS

This study provides evidence regarding central bank intervention activity in an emerging market via an electronic limit order book. Thus we contribute to the increasingly important field of interventions in emerging markets but we also contribute – due to unusually detailed data – to measuring the precise impact that interventions may have in modern electronic currency markets.

We have focused on a short period of 2002 when the Russian Central Bank maintained a exchange rate band for the rouble price of a dollar by posting limit orders on an electronic crossing network. The central bank orders were very large relative to the market and served as a credible signaling device to private market participants.

Due to available deep information about the order book, we are able to analyze this widespread exchange rate arrangement in a way not being tackled in the earlier literature.[26] We find for our sample that trades at the central bank's limit price simultaneously induce a downward shift in volatility on a daily frequency, i.e. they reduce the overall level of volatility. However, at the intraday frequency, such trades induce a higher transitory volatility that lasts for a few minutes. The same results hold for spreads, although the transitory effects on bid-ask spreads are weaker than for return volatility. The dampening effect of trades associated with defense of the exchange rate band can also be recognized from the lower price impact of order flow on days when the central bank is an active participant in the market. There is evidence of a stabilizing effect as the price impact falls the closer price is to the central bank's limit. Clearly, central bank policy must be credible, which is supported here by the very large limit orders. It would be interesting to know whether our finding holds in different samples.

Finally, we see from the intraday order choice analysis that more informed traders expect – in line with fundamentals and correctly in retrospect – a further decline of the rouble since they trade aggressively against the upper limit of the exchange rate band. This is in contrast to the behavior of the uninformed and is consistent with rational speculation from informed traders in combination with an intervention policy to successfully calm the market. It is likely that the central bank seeks to smooth the path of rouble depreciation in a crawling peg arrangement rather than defend a rigid peg at some particular exchange rate.

[26] Findings are not driven by particular characteristics of the Russian market as the daily interbank trading session at the MICEX has characteristics like those of other electronic crossing networks.

Since market participants know the size of trades that occurred, the central bank's reserve losses from trades at its offer price, i.e. $338 million over the week under study, are easily calculated. This transparency of the central bank's position is one potential disadvantage of using such a mechanism to limit exchange rate changes. However, there may be an informational counterweight in that the central bank also learned who was trading at their limit price as after each trade is completed, the parties learn each other's identity. So the central bank could potentially use moral suasion or other means to discipline any private banks that might be viewed as abusing the system or contributing to a speculative attack.

The provision of liquidity via an electronic limit order book is only likely to serve as an effective exchange rate limiting device in a market where over-the-counter trading is small compared to the electronic market and liquidity is concentrated on one trading platform. In the case of Russia, non-residents traded in an offshore market due to a lack of full convertibility of the rouble so that the domestic market was segmented from outside pressures. This allowed the central bank to effectively facilitate a crawling exchange rate band using limit orders.

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Table 1. Descriptive statistics

Panel A: Descriptive statistics per day

Day of March	Stdev	Obs	max price	min price	trades at CB ask	trades at CB bid	trading volume	number of trades	average trading volume
1	5.01	3,548	30.9600	30.9400	299	109	95,336,000	1,470	64,854
4	4.95	3,405	30.9950	30.9420	922	0	165,000,000	1,653	99,819
5	1.27	4,049	30.9950	30.9855	13	0	83,964,000	1,593	52,708
6	0.61	3,392	30.9950	30.9920	748	0	165,000,000	1,639	100,671
7	1.31	3,334	30.9950	30.9851	602	0	212,000,000	1,555	136,334
11	5.58	3,372	31.0720	30.9950			69,543,000	1,258	55,281
12	1.57	4,281	31.0632	31.0504			94,964,000	1,640	57,905
13	2.19	4,235	31.0840	31.0600			74,905,000	1,621	46,209
14	7.52	4,715	31.0720	31.0050			65,768,000	1,649	39,884
15	4.92	4,523	31.0900	31.0250			82,350,000	1,571	52,419
18	7.25	4,499	31.1200	31.0701			65,267,000	1,575	41,439
19	3.64	4,324	31.1400	31.1175			69,565,000	1,582	43,973
20	2.89	4,446	31.1449	31.1285			94,152,000	1,686	55,843
21	4.23	4,047	31.1499	31.1151			80,408,000	1,527	52,657
22	4.21	4,485	31.1400	31.0999			77,721,000	1,674	46,428

Panel B: Descriptive statistics for intervention versus non-intervention days

Days of March	stdev	obs	max price	min price	trades at ask	trades at bid	trading volume	number of trades	average trading volume
1 to 7	3.24	17,728	30.9950	30.9400	2584	109	720,000,000	7910	91,024
11 to 21	4.89	38,442	31.1499	30.9950			697,000,000	14109	49,401

Panel C: Volatility tests

H_0: $\sigma_{\text{intervention days}} = \sigma_{\text{non-intervention days}}$ (all events)	**(0.00)
H_0: $\sigma_{\text{intervention days}} = \sigma_{\text{non-intervention days}}$ (all events off the quote)	**(0.00)

Notes: Panel A shows descriptive statistics for each day of our sample. March 1st to 7th are days with major central bank intervention, March 22nd only has a few very minor interventions from the central bank. Columns "stdev" and "obs" show the sample standard deviation of midquote returns and the number of observations on a given day. The next two columns show the maximum and minimum price. Trades at CB ask (bid) shows the number of trades at the ask (bid) quote of the central bank. All volumes are expressed in USD. Panel B shows the same descriptive statistics for all days in the respective two main blocks of our sample: March 1st to 7th (major intervention days) versus March 11th to March 21st (non-intervention days). Panel C shows p-values for the test that the standard deviation of midquote returns is the same on intervention days and non-interventions days. The test is based on Newey-West HAC robust standard errors. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Table 2. Order and trade activity of the central bank and private banks

	Central Bank	Private Banks
Limit orders submitted	11	6,626
Number of trades initiated	7	7,910
Median limit order size	$50,298,000	$30,000
Maximum limit order size	$151,000,000	$45,000,000
Minimum limit order size	$6,000,000	$1,000
Median trade size	$210,000	$20,000
Maximum trade size	$45,000,000	$7,995,000
Minimum trade size	$100,000	$1,000

Notes: The data summarize all trade and order activity of the Russian central bank and private banks active on the interbank SELT system over the period March 1 to March 22, 2002.

Table 3. FX spot rate volatility

	Dependent: standard deviation			Dependent: high-low range		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Share CB_{-1}	0.11 **[2.92]	0.12 **[2.82]	0.08 *[2.52]	0.19 **[2.69]	0.17 **[2.88]	0.11 *[2.21]
Share CB_{-2}	0.10 **[3.81]	0.11 **[3.70]	0.07 *[2.53]	0.12 *[2.05]	0.15 **[2.70]	0.04 *[2.19]
Share CB_{-3}	0.10 **[2.63]	0.10 *[2.49]	0.06 [1.61]	0.07 [1.89]	0.08 *[1.99]	-0.01 [-0.67]
Share CB_{-4}	0.02 [0.68]	0.01 [0.58]	-0.03 [-0.33]			
CB-day	-0.49 **[-13.85]	-0.48 **[-12.36]	-0.27 **[-6.87]	-0.17 **[-7.11]	-0.17 **[-7.13]	-0.14 **[-6.99]
$volatility_{-1}$			0.14 **[4.34]			0.24 **[4.32]
$volatility_{-2}$			0.08 [1.81]			0.10 *[1.98]
mean $spread_{-1}$			0.01 **[3.43]			0.02 **[2.83]
mean $spread_{-2}$			-0.00 [-0.83]			-0.01 [-0.92]
$volume_{-1}$			0.04 *[2.07]			0.02 *[2.14]
$volume_{-2}$			-0.02 [-1.59]			0.00 [1.32]
time		-0.02 **[-3.72]	-0.00 [-1.14]		-0.01 **[-3.01]	-0.01 *[2.04]
$time^2 \times 10^{-2}$		0.03 **[4.00]	0.00 [1.47]		0.03 **[3.26]	0.01 *[2.10]
constant	0.60 **[21.53]	0.63 **[10.02]	0.26 **[5.42]	0.22 **[4.64]	0.23 **[4.09]	0.17 [3.91]
adj. R^2	0.09	0.12	0.24	0.10	0.14	0.17
AIC	1.35	1.33	1.10	0.31	0.28	0.24
obs	1,740	1,740	1,740	1,740	1,740	1,740

Notes: This table shows regression results where the dependent variable is the midquote return standard deviation in specifications (i) to (iii) and high-low range in specifications (iv) to (vi). The sampling frequency is 30 seconds. T-statistics based on Newey-West HAC standard errors in parentheses. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Table 4. Mean bid-ask spreads

	Dependent: Mean spread		
	(i)	(ii)	(iii)
Share CB_{-1}	2.40 **[3.07]	2.68 **[3.00	1.62 *[2.23
Share CB_{-2}	1.35 **[2.65]	1.46 **[2.48	0.20 [0.40]
Share CB_{-3}	1.12 [1.46]	1.08 [1.25]	0.31 [0.52
Share CB_{-4}			
CB-day	-9.13 **[-11.40	-9.54 **[-8.32]	-2.32 **[-3.55]
$volatility_{-1}$			-0.09 [-0.13
$volatility_{-2}$			-0.51 [-0.82
mean $spread_{-1}$			0.78 **[10.42]
mean $spread_{-2}$			0.06 [1.31]
$volume_{-1}$			0.62 *[2.05]
$volume_{-2}$			-0.52 [-1.52]
time		-0.61 **[-4.17]	-0.04 [-0.97]
$time^2 \times 10^{-2}$		1.03 **[3.92]	1.70 *[2.20]
constant	13.92 **[13.20]	15.10 **[7.99]	2.96 [1.20]
adj. R^2	0.06	0.15	0.62
AIC	7.66	7.55	6.32
obs	1,755	1,755	1,755

Notes: This table shows regression results with the mean bid-ask spread as dependent variable. The sampling frequency is 30 seconds. T-statistics based on Newey-West HAC standard errors in parentheses. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Table 5. Price impact of order flow

	Unadjusted order flow					Unexpected Order flow		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
OF_t	0.087 **[6.99]	0.123 **[9.14]	0.087 **[7.49]	0.123 **[9.12]	0.121 **[8.67]	0.112 **[7.88]	0.171 **[8.14]	0.159 **[6.95]
OF_t×(CB-day)		-0.083 **[-3.85]		-0.096 **[-3.79]	-0.100 **[-4.33]		-0.160 **[-4.32]	-0.118 **[-5.04]
OF_t×(CB-day)×Dist			-1.685 [-0.31]	10.327 *[1.98]	11.15 *[2.04]			9.79 *[2.18]
Δm_{-1}					0.089 [1.57]			
Δm_{-2}					-0.026 [-1.08]			
OF_{t-1}					0.011 [1.38]			
OF_{t-2}					0.003 [0.31]			
const.	-0.480 **[-7.39]	-0.433 **[-7.21]	-0.482 **[-7.49]	-0.414 **[-7.04]	-0.436 **[-6.87]	-0.390 **[-6.48]	-0.359 **[-4.99]	-0.362 **[-5.13]
adj. R^2	0.11	0.14	0.11	0.15	0.15	0.12	0.14	0.16
obs	1,800	1,800	1,800	1,800	1,770	1,800	1,800	1,800

Notes: The table shows regression results of midquote returns on order flow and further controls. The left panel (i) – (v) shows results for the usual order flow indicator, whereas the right panel (vi) – (viii) shows results for a measure of unexpected order flow. The sampling frequency is 30 seconds. T-statistics based on Newey-West HAC standard errors in parentheses. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Table 6. Permanent price impacts under different market conditions

Price Impacts (×1,000)		
	CB-days	Non-CB-days
All trades	0.721 [0.000; 1.442]	1.444 [0. 664; 2.224]
Low volume	0.547 [-0.101; 1.194]	1.057 [0.303; 1.811]
High volume	0.836 [-0.042; 1.741]	2.053 [0.716; 3.390]
Low volatility	0.140 [-0.198; 0.478]	0.651 [0.257; 1.045]
High volatility	1.742 [0.021; 3.464]	1.899 [0.613; 3.185]
Low spreads	0.242 [-0.194; 0.678]	0.954 [0.318; 1.590]
High spreads	1.211 [-0.248; 2.670]	2.101 [0.453; 3.749]

Notes: The table shows permanent price impacts from order flow on midquote returns. Permanent price impacts are measured according to the SVAR in equations (4) and (5). The sampling frequency is 30 seconds. 95% bootstrap confidence intervals are shown in squared brackets.

Table 7. Trading direction of different market participants

	Traders from Moscow and St. Petersburg	Traders from Periphery
constant	0.39 **(0.00)	0.38 ** (0.00)
Distance (from CB's ask)	-7.59 ** (0.00)	3.82 *(0.04)
Momentum	0.47 ** (0.00)	0.26 (0.17)
Learning	2.69 ** (0.00)	1.46 ** (0.00)
Ask volume	0.03 (0.41)	0.01 *0.03)
Bid volume	0.01 (0.65)	-0.01 **(0.00)
Time	7.87 ** (0.00)	-3.90 (0.06)
McFadden R^2	0.07	0.03
AIC	1.18	1.34
SIC	1.19	1.37
Log likelihood	-2385.79	-863.64
Restr. log likelihood	-2573.00	-891.37
LR statistic (6 df)	374.41	55.46
Probability(LR stat)	**(0.00)	**(0.00)

Notes: The table shows results from logit regression models where the dependent variable is coded as one when an order is a buy order and zero when it is a sell order. The sampling frequency is event time. Bootstrap p-values based on 250 replications in parentheses. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Figure 1. Reserves of industrialized and developing countries

The vertical axis shows the share of total reserves held by industrialized (solid, black) and developing (dashed, grey) countries, respectively. Calculations are based on IMF data.

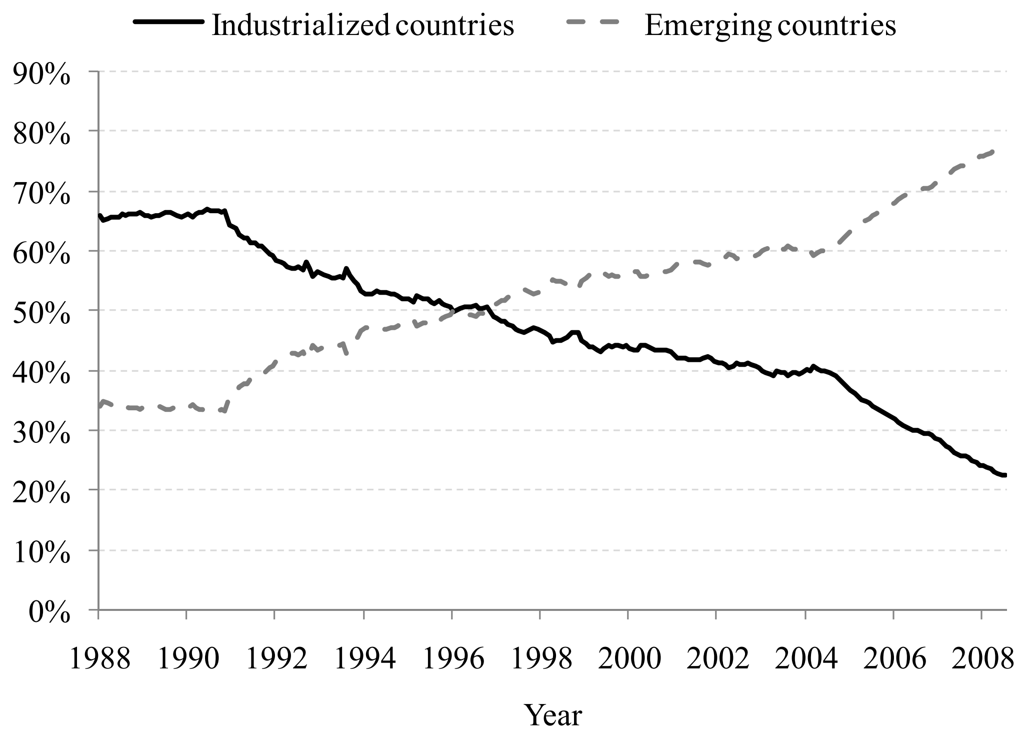


Figure 2. Share of countries with various exchange rate arrangements

This figure shows the share of countries adopting a crawling peg or band relative to all countries with available data (solid black line) and the share of countries adaopting freely or managed floating (dashed grey line). Calculations are based on the classification by Reinhart and Rogoff (2004) and the raw data underlying are provided on the web page of Carmen Reinhart.

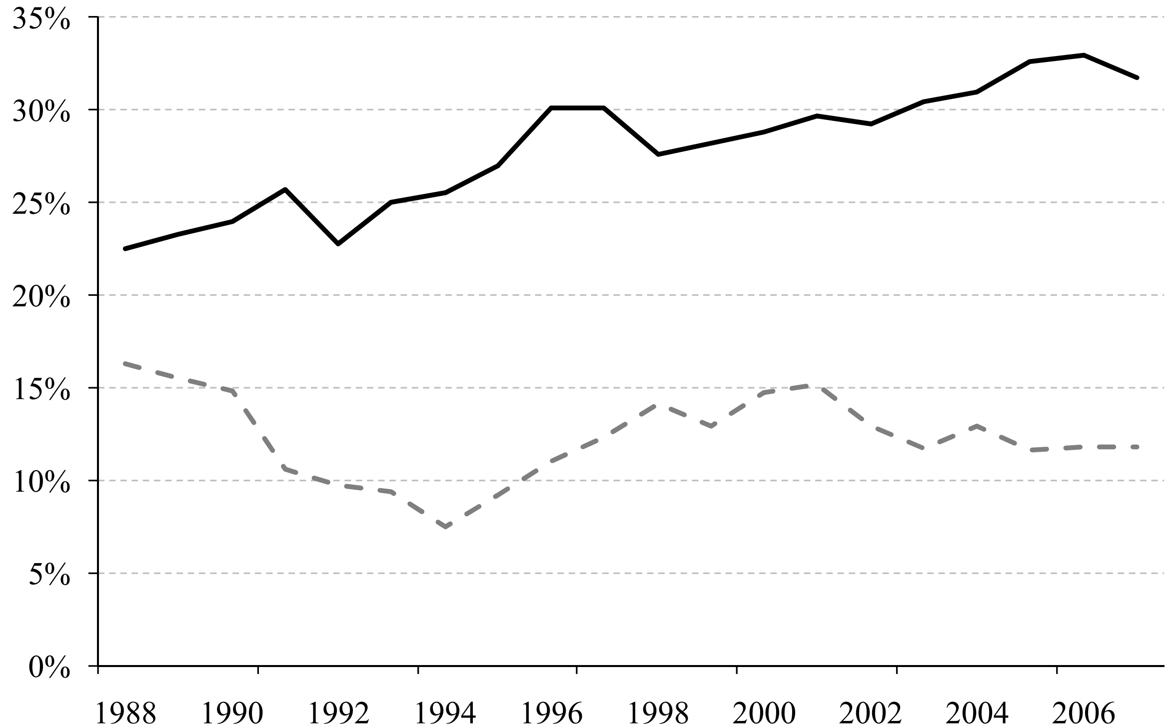


Figure 3: Exchange rate, roubles per dollar
The official rouble price of the dollar is plotted for the first half of 2002. The period of central bank intervention studied in this paper is indicated by the vertical lines in the chart.

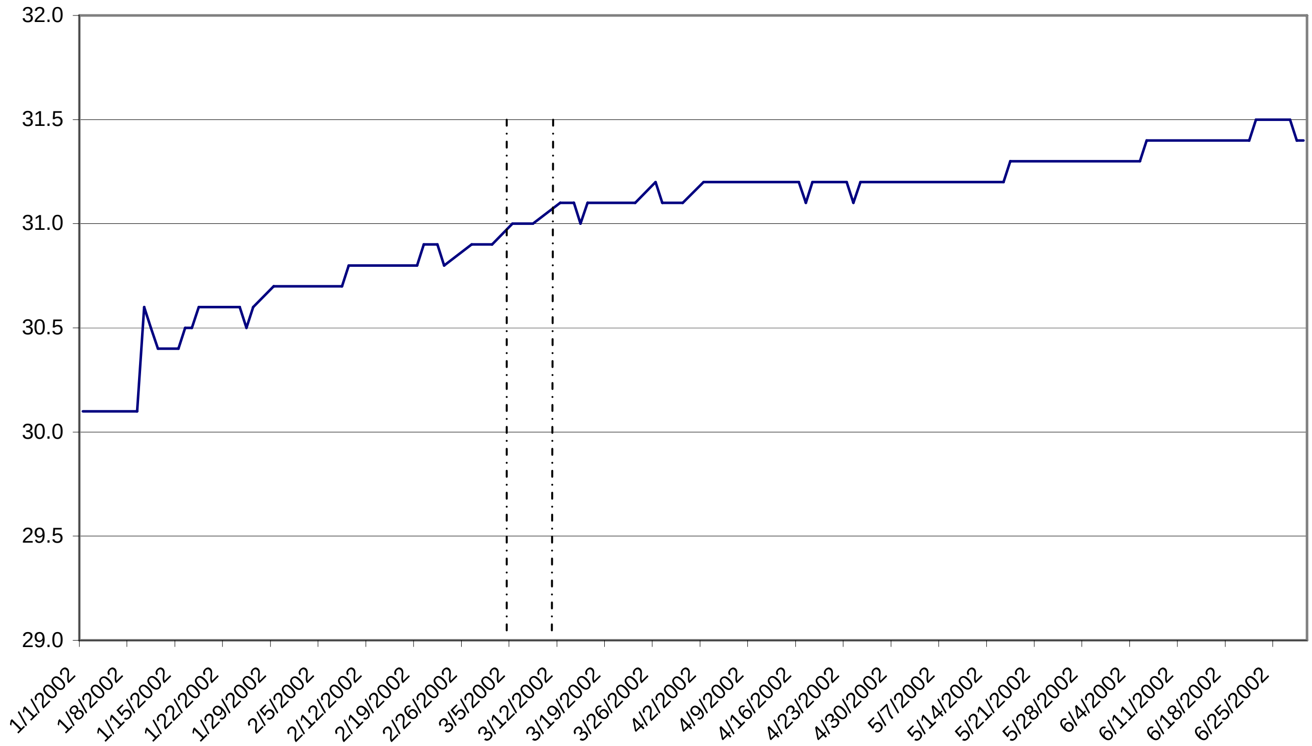
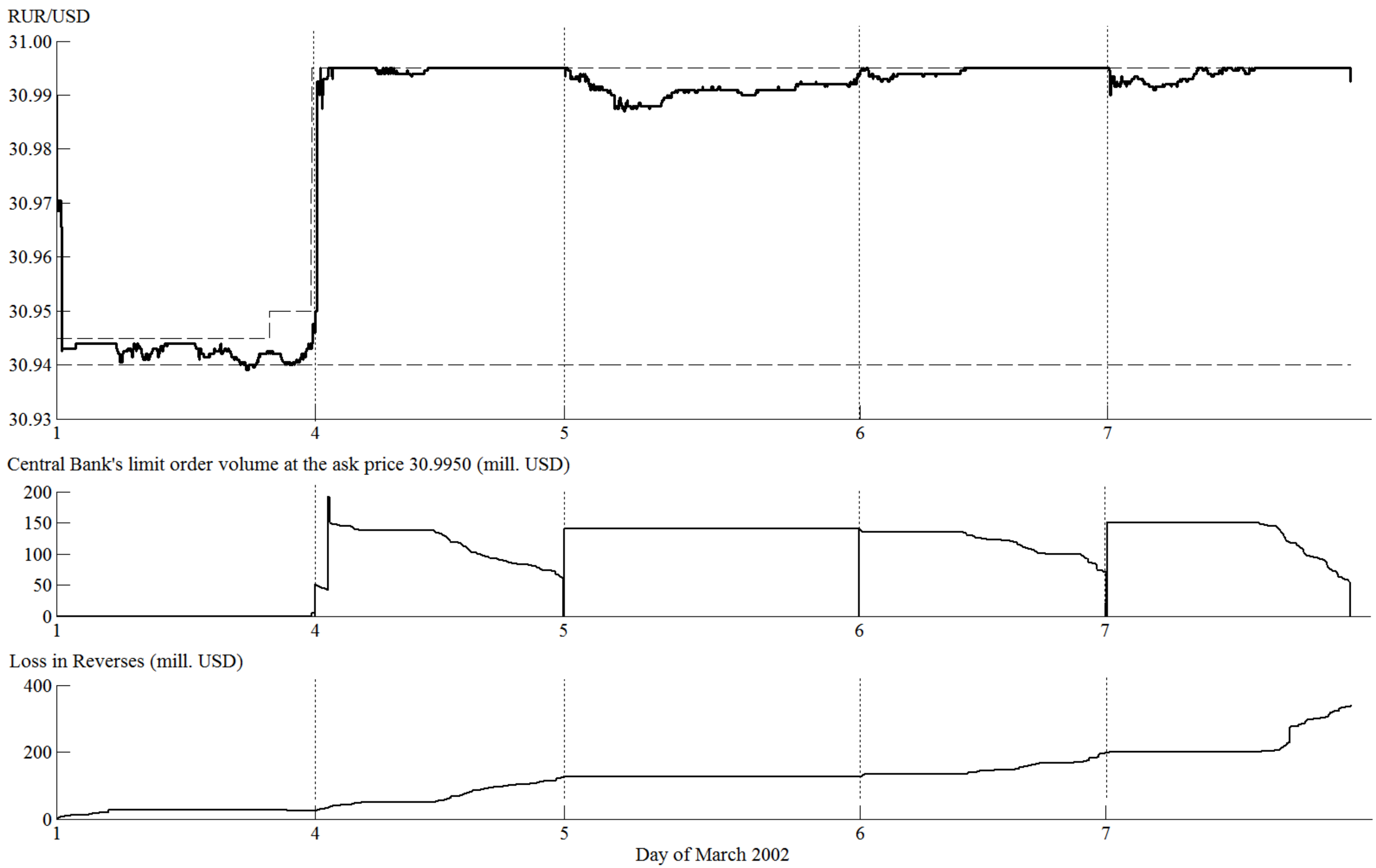


Figure 4: Central bank limit orders and cumulative reserve loss
The upper figure illustrates the central bank's order at a price of 30.9450 for March 1 and 30.9950 for March 4-7, along with the actual price of executed deals in the market. Note that the central bank's bid price is held fixed at 30.9400, on March 1 there were several trades at this bid. The middle panel illustrates the quantity on offer at the central bank's limit price for March 4-7 while the lower panel shows the cumulative loss of dollar reserves as a result of central bank trades.



Appendix 1. GARCH(1,1)-model of spot rate volatility

	(i)	(ii)	(iii)	(iv)
Mean equation				
Const.	-0.03 [-0.95]	-0.0 [-0.13]	-0.01 [-0.22]	0.00 [0.01]
Order flow				0.079 **[6.14]
Variance equation				
Const.	2.03 **[6.56]	3.47 **[11.79]	3.38 **[4.01]	3.33 **[5.84]
ε^2_{t-1}	0.31 **[4.26]	0.15 **[4.24]	0.21 **[3.84]	0.13 **[5.47]
σ^2_{t-1}	0.66 **[8.25]	0.59 **[11.31]	0.35 **[5.12]	0.36 **[5.51]
CB-day		-3.37 **[-9.01]	-3.01 **[-6.93]	-3.30 **[-8.62]
$Share_{t-1}$		-0.18 **[3.57]	-0. 17 **[-2.57]	-0.13 **[-2.83]
$Share_{t-2}$		-0.07 *[-2.02]	-0.11 [-1.03]	-0.05 *[-1.99]
Trading control variables	NO	NO	*YES	*YES
Time dummies	**YES	**YES	**YES	**YES
ν	3.19	4.90	4.99	6.26
Adj. R^2	-0.01	-0.00	-0.01	0.10
obs	1,798	1,798	1,798	1,798

Notes: The table shows results from GARCH(1,1) models for midquote returns where error terms are assumed to follow a student's t-distribution (ν denotes the degrees of freedom parameter of the t-distribution). "Trading control variables" include lagged bid-ask spreads and lagged trading volume (two lags). "Time dummies" are dummy variables for non-overlapping intervals of five minutes. Included are eleven dummies for trading intervals 1-5, 5-10, … , 51-55. Stars refer to the level of significance, *: 5%-level, **: 1%-level.

Appendix 2. Order aggressiveness of different market participants

	Traders from Moscow and St. Petersburg	Traders from Periphery
constant	0.15	-0.37
	**(0.00)	**(0.00)
Distance (from CB's ask)	-4.39	4.39
	**(0.00)	**(0.00)
Momentum	0.06	0.41
	(0.63)	*(0.03)
Learning	1.24	1.31
	**(0.00)	**(0.00)
Same side volume	-0.08	0.01
	**(0.00)	*(0.02)
Other side volume	0.01	-0.01
	**(0.00)	**(0.00)
Spread	1.32	1.46
	*(0.05)	(0.10)
Volatility	-1.85	-2.60
	(0.14)	(0.09)
Time	17.54	12.36
	(0.00)	**(0.00)
McFadden R^2	0.03	0.02
AIC	1.31	1.33
SIC	1.32	1.35
Log likelihood	-4847.39	-2055.68
Restr. log likelihood	-5003.88	-2107.49
LR statistic (6 df)	312.97	103.62
Probability(LR stat)	**(0.00)	**(0.00)

Notes: The table shows results from logit regression models where the dependent variable is coded as one when an order is a market order and zero if the order is a limit order. The sampling frequency is event time. Bootstrap p-values based on 250 replications in parentheses. Stars refer to the level of significance, *: 5%-level, **: 1%-level.