Inside the Black Box: Why are Order Flows Models of Exchange Rate more competitive than Traditional Models of Exchange Rate?

Gabriele Di Filippo

Department of Economics, LEDA-SDFi, University Paris Dauphine

Preliminary Version: October 2009
Revised Version: January 2011

Abstract

This article looks inside the black box of order flows to understand why order flows models of exchange rate are more competitive than traditional models of exchange rate. We set a theoretical model that relies on a behavioural exchange rate model and a microstructure model. The model puts forward three results. First, simulations replicate stylised facts observed in the foreign exchange market. Secondly, the model shows that the foreign exchange market is intrinsically inefficient. Incoming information is distorted by behavioural noise and microstructure noise. Thirdly, order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle. Indeed, order flows contain processed information i.e. a time-varying weight of fundamental information, behavioural information and microstructure information while traditional models only consider raw information i.e. fundamental information.

Keywords: Behavioural Finance, Microstructure, Order Flows Models, Market Efficiency, Exchange Rate Disconnection Puzzle

JEL Codes: F31, G1, G15

1 Author Contact: gabriele.di_filippo@yahoo.fr; University Paris IX Dauphine, Office B313, Place du Maréchal de Lattre de Tassigny 75775 Paris CEDEX 16, France; Acknowledgements: I am grateful to helpful comments from the participants of the PhD seminars in financial macroeconomics organised by the doctoral school of the University Paris IX Dauphine and to participants at the workshop “Market Microstructure: confronting many viewpoints” organised by the Institut Louis Bachelier. I am very grateful to two anonymous referees at the journal Finance. All the remaining errors are of the author only.
1. Introduction

Following decades of empirical failure to explain and forecast exchange rates dynamics based on traditional exchange rate models (Meese and Rogoff, (1983), Cheung et al. (2005)), the recent microstructure literature offers promising results. Microstructure models based on order flows provide better explanatory and predictive powers in forecasting exchange rate dynamics than traditional models; especially at short horizons (Evans and Lyons (2002a, 2002b), Danielsson et al. (2002), Berger et al. (2008), Chinn and Moore (2008)). To justify this performance, order flows theorists claim that order flow includes private information about exchange rate fundamentals (Lyons (2001), Evans and Lyons (2008), Chinn and Moore (2008), Rime, Sarno and Sojli (2010)). However, many studies counter this view. Such studies show that order flows only convey information about liquidity effects, temporary preferences and other demand shocks. Both views raise a debate between respectively the proponents of the strong flow centric view and the ones of the weak flow centric view.

This paper defends the idea that order flows contain information from both the strong and the weak flow centric view; but not solely. The article investigates inside the black box of order flows to unveil the various types of information contained in order flows. This question is becoming increasingly important as the black box has been shifted from understanding exchange rate determination to understanding order flow determination. We set a theoretical model of the foreign exchange market that describes how the initial information arriving to market agents is embedded into the final price of the currency.

The most related studies to this paper are Bachetta and Van Wincoop (2006) and Evans (2010). Bachetta and Van Wincoop (2006) provide an analytical framework which regroups both the strong and the weak flow centric views. Their main finding is that information heterogeneity disconnects the exchange rate from observed macroeconomic fundamentals in the short run, while there is a close relationship in the long run. At the same time, there is a close link between exchange rate dynamics and order flows over all horizons. Evans (2010) presents a theoretical model to analyse the links between high frequency spot exchange rates, order flows and macroeconomic developments. Evans finds that trades between dealers and customers convey information to dealers about the current state of the economy which dealers then use to revise their spot exchange rate quotes.

The model presented here departs from Bachetta and Van Wincoop (2006) and Evans (2010) in several ways. Indeed, both models miss a major component of exchange rate determination in the short run: agents’ behaviours (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004)). Our modeling approach integrates not solely the public and private information as in Bachetta and Van Wincoop (2006) and Evans (2010) but also behavioural components affecting customers and dealers decisions. Our model therefore merges two strands of the literature: behavioural exchange rate models and microstructure models of exchange rate. The model puts forward three results. First, simulations replicate important stylised facts observed in the foreign exchange market. In the short run, the exchange rate is disconnected from its fundamentals but not from order flows. In the long run, the exchange rate returns towards its fundamental value and remains still close to order flows. Customer and interdealer order flows are highly correlated with exchange rate dynamics at all horizons. Besides the hot potato effect magnifies the amount of interdealer order flows relative to the amount of customer order flows. Secondly, the model indicates that the foreign exchange market is intrinsically inefficient. The introduction of incoming information in the final price of the currency is distorted by agents’ behaviours (behavioural noise) and by the trading mechanism peculiar to the foreign exchange market (microstructure noise). Thirdly, the model explains why order flows provide an answer to the
exchange rate disconnection puzzle. Order flows contain information processed by agents while traditional models only consider raw information. Processed information includes a time-varying weight of fundamental information (both public and private), behavioural information (both public and private) and microstructure information. Conversely, information considered in traditional models only includes public fundamental information. The difference in the types of information considered by order flows models and traditional models explain why order flows models provide higher explanatory and predictive powers of exchange rate dynamics relative to traditional models.

The remainder of the paper comprises 5 sections. Section 2 provides evidence of the high explanatory and predictive powers of order flows models. Section 3 proposes a literature survey concerning the information contained in order flows. Section 4 presents a theoretical model of the foreign exchange market and exposes the simulations provided by the model. Section 5 addresses the question of foreign exchange market efficiency and explains why order flows models come as a resolution to the exchange rate disconnection puzzle. Section 6 concludes.

2. On the competitive performances of order flows models of exchange rate

In a pioneering work, Evans and Lyons (2001, 2002) came up with an hybrid model based on private information and public information to explain exchange rate dynamics. The hybrid model takes the following form:

\[
\Delta s_t = \beta_0 + \beta_1 \Delta(i_t - i^*_t) + \beta_2 \Delta X_t + \epsilon_t
\]

With \(s_t\), the (log of) the spot exchange rate (an increase in \(s\) is equal to an appreciation of the domestic currency); \((i_t - i^*_t)\), the interest rate differential between the domestic and the foreign country; \(X_t\), the net cumulated order flow. \(\Delta\) stands for the first difference of the series.

Macroeconomic fundamentals (here the interest rate differential \((i_t - i^*_t)\)) represents public information known by all agents. Order flows \(\Delta X_t\) represent private information known by a minority of agents. Order flow is defined as the net of buyer- and seller-initiated currency transactions. Intuitively, order flow represents a willingness to back one's beliefs on future exchange rate dynamics, with real money.

Evans and Lyons tested their model on the deutsche mark/dollar, yen/dollar and pound/dollar in daily frequency from May 1996 to August 1996. They show that private information (order flows) explain at best 65% of the variance of exchange rates. On the contrary, public information (the interest rate differential) only explains at best 5% of the variance of exchange rates (a figure close to the ones obtained with traditional exchange rate models). Similar results can be found in the literature as shown in table 1.

---

A detailed description of order flows is available in appendix A.
Table 1: Literature survey of the in-sample performance of order flows models

<table>
<thead>
<tr>
<th>Authors</th>
<th>Period</th>
<th>Frequency</th>
<th>Exogenous</th>
<th>Explanatory Power (R²)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Evans and Lyons (2002a)</td>
<td>May 1996 - August 1996</td>
<td>Daily</td>
<td>Interdealer order flow</td>
<td>Deutschmark/Dollar 0.67</td>
<td>Yen/Dollar 0.43</td>
</tr>
<tr>
<td>Evans and Lyons (2002b)</td>
<td>May 1996 - August 1996</td>
<td>Daily</td>
<td>Interdealer order flow</td>
<td>Pound/Dollar 0.29</td>
<td>Swiss Franc/Dollar 0.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Pound/Dollar 0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Euro/Pound 0.01</td>
</tr>
<tr>
<td>Berger et al. (2008)</td>
<td>January 1999 - December 2004</td>
<td>Daily</td>
<td>Interdealer order flow</td>
<td>Euro/Dollar 0.46</td>
<td>Yen/Dollar 0.54</td>
</tr>
<tr>
<td>Berger et al. (2008)</td>
<td>January 1999 - December 2004</td>
<td>Weekly</td>
<td>Interdealer order flow</td>
<td>Euro/Dollar 0.43</td>
<td>Yen/Dollar 0.48</td>
</tr>
<tr>
<td>Berger et al. (2008)</td>
<td>January 1999 - December 2004</td>
<td>Monthly</td>
<td>Interdealer order flow</td>
<td>Euro/Dollar 0.21</td>
<td>Yen/Dollar 0.34</td>
</tr>
</tbody>
</table>

NB: The regression method used in the studies mentioned in Table 1 is ordinary least squares (OLS).

Table 1 shows that the explanatory power of order flows model far exceeds the one of traditional models of exchange rate. For daily and weekly frequencies, the coefficients of determination (R²) spread between 30% and 67% (except for Danielsson et al. (2002)). At such frequencies, traditional exchange rate models usually provide R² close to or less than 10%. Beyond the explanatory performance of exchange rates, order flows provide also better exchange rate forecasts than traditional models. Numerous studies show that order flows models beat the random walk in the short run (Evans and Lyons (2001, 2002a, 2002b, 2005, 2006), Lindahl and Rime (2006), Rime et al. (2010)).

The results from order flows models have to be put into perspective. The relationship between order flows and exchange rate dynamics is strong at intradaily, daily and weekly frequencies but declines at lower frequencies. For example, Table 1 shows that in Berger et al. (2008) order flows explain about 50% of the variance of exchange rates at daily and weekly frequencies. At lower frequencies, for instance monthly frequencies, the R² declines gradually and falls to 34% for the yen/dollar exchange rate and to 21% for the euro/dollar exchange rate. The same observation stands in Chinn and Moore (2008). Therefore the explanatory power of exchange rate variation by order flows models falls at monthly frequencies. In some cases, the explanatory power comes even close to the one offered by traditional exchange rate models (see Chinn and Moore (2008)) while in other cases the explanatory power is still higher than the explanatory power of traditional exchange rate models based on
3. The informational content of order flows: a literature review

According to Lyons (2001), order flow contains private information. Private information can be split into three components: fundamental information, liquidity effects and portfolio balance effects.

Fundamental information includes private information about exchange rate fundamentals. For example, if a central bank intervenes in the foreign exchange market by transmitting a positive order flow to a market-maker, then this market-maker will infer a likely appreciation of the currency. Fundamental information is supposed to have a permanent effect on currency prices.

Inventory or liquidity effects refer to information about transfers of unwanted currency positions between market-makers. For instance, if a market-maker A has to absorb a large stock of currencies from a market-maker B, the market-maker A will bear more risks (mainly liquidity and valuation risks). As a result, the market-maker A will ask a higher risk premium (hence a lower price) to buy the currencies of market-maker B. This risk premium will only have a transitory effect on the price of the currency since it will disappear after the trade between the two market-makers. Thus inventory effects only have transitory effects on currency prices.

Portfolio balance effects relates to agents’ decisions independently of fundamental movements. For example, an import-export firm can operate in the market to convert foreign currencies in domestic currencies independently of fundamental movements. The effect of portfolio balance is assumed to be permanent on currency prices.

A lot of studies have analysed the informational content of order flows. The literature is split between two separate views: the strong flow centric view and the weak flow centric view.

The strong flow centric view states that order flows contains in majority fundamental information. Order flows are correlated with news about exchange rate fundamentals and have thus a permanent effect on currency prices (Ito et al. (1998), Rime (2000), Evans and Lyons (2001, 2002, 2005a, 2008), Love and Payne (2004), Marsh and O’Rourke (2005)). Love and Payne (2004) base their study on intraday interdealer order flows on the euro/dollar, dollar/pound and pound/euro, from the 28th September 1999 to the 24th July 2000. They show that “even information that is publicly and simultaneously released to all market participants is largely impounded into prices via the key micro-level price determinant - order flow”. Love and Payne find that between a half and two-thirds of price relevant information is incorporated into prices via order flows.

Marsh and O’Rourke (2005) use daily customer order flows from August 2002 to June 2004 on bilateral exchange rates between the dollar, the euro, the pound and the yen. They

3 Recently, Carlini et al. (2010) show that in the long run (about 5 years), the cointegration relationship between order flows and stock prices is not significant. However by using more suitable tools, they show that order flows and stock prices are fractionnally cointegrated or even still cointegrated if we correct order flows by the volumes of transactions in the market.
show that inventory effects play a minor role in the informational content of order flows. A major role is attributed to fundamental effects. Particularly, when decomposing order flows by types of clients, they show that coefficients associated to leveraged firms such as hedge funds are very large compared to other flows (such as flows coming from unleveraged firm (mutual funds) and non-financial corporations (multinationals)). They conclude that flows coming from leveraged funds are more informative about fundamentals than flows coming from other customers.\footnote{The view of Marsh and O’Rourke (2005) may be confirmed by Corsetti et al. (2001) who claim that a lot of operators believe that hedge funds have an informational advantage relative to the rest of the market concerning asset prices. However another interpretation of the high coefficients associated to order flows coming from hedge funds could be related to the fact that hedge funds speculate aggressively and thus produce huge movements in the market and hence in currency prices. Therefore order flows from hedge funds would be more related to speculative forces rather than to exchange rate fundamentals (Wei and Kim (1998)). Survey results among practitioners reinforce this argument since speculative forces are considered as a major determinant of exchange rates at short run horizons (Cheung and Wong (2000), Cheung and Chinn (2001) and Cheung, Chin and Marsh (2004)).}

Evans and Lyons (2008) estimate an intraday model using interdealer order flows on the deutschemark/dollar market from May 1 to August 31, 1996. They show that roughly two-thirds of the total effect of macro news on the deutschemark/dollar exchange rate is transmitted \emph{via} order flows. They claim that order flows contribute significantly to changing currency prices at all times, but that they contribute more to changing prices immediately after news arrivals about fundamentals.

Rime, Sarno and Sojli (2010) uses daily interdealer order flows for the euro, the pound and the yen against the dollar between February 13, 2004 and February 14, 2005. They argue that news about macroeconomic fundamentals are important determinants of order flows. They find that “order flow is intimately linked to both news on fundamentals and to changes in expectations about these fundamentals”.

According to the weak flow centric view order flows do not transmit private information about fundamentals in currency prices. Rather, order flows convey information about liquidity effects, temporary preferences and other demand shocks. Order flows have thus a transitory effect on asset prices. Evidence for the weak flow centric view is based on results provided by econometric analyses as well as survey studies.

Concerning survey studies, Cheung, Chinn and Marsh (2004) base their analysis on a sample of UK-based foreign exchange dealers in March/April 1998. They found that after analysing order flows, “traders do not vary their bid-ask spread either very often or for some of the reasons thought important in the microstructure literature”. Microstructure theory suggests that three main factors can lead traders to change their spreads: liquidity effects, portfolio balance effects and fundamental information. Cheung et al. (2004) add that “traders were asked their reasons for changing their quoted spreads from the market convention and results suggest that the liquidity effect is dominant. This was confirmed in conversations with traders”.

In the same vein, Gehrig and Menkhoff (2006) sent questionnaires to professional market participants in Germany in July 1992. They show that “flows are more informative about semifundamental private information. In other words, order flows contain information about short-term trading objectives or liquidity considerations of other traders that may affect short-term price movements, but that will not affect medium-term asset prices. Such information may be interim price relevant but irrelevant in the long run”. Gehrig and Menkhoff add that “flow analysis does not seem to be used as a tool to learn about the fundamental information”.

\textsuperscript{4}

Froot and Ramadorai (2005) analyse a sample of daily institutional investor flows transactions for 18 exchange rates against the US dollar from June 1994 to February 2001. They show that order flows have a transitory impact on exchange rates and do not convey information about macroeconomic fundamentals to market-makers. “Flows appear to be bound up with transitory currency under- and overreactions, but unrelated to the permanent component of exchange rate surprises. Yet, these exchange rate surprises are strongly related to important fundamental variables, as predicted by theory”.

Berger et al. (2008) analyse monthly interdealer order flows from January 1999 to December 2004 on the euro/dollar and the yen/dollar exchange rates. Their analysis points to an important role for liquidity effects in the relationship between order flows and exchange rates. They provide evidence that the relationship between order flows and exchange rates is strong at daily and weekly frequencies but weakens significantly from monthly frequencies.

Chinn and Moore (2008) analyse monthly interdealer order flows from January 1999 to January 2007 for the dollar/euro and dollar/yen exchange rates. They build an exchange rate model based on a combination of the traditional monetary model of exchange rate and the Evans-Lyons microstructure approach. They show that “cumulative order flow tracks liquidity shocks and provides the ‘missing link’ to augmenting the explanatory power of conventional monetary models”.

This paper defends the idea that order flows contain information from both the strong and the weak flow centric view; but not solely. The article investigates inside the black box of order flows to disentangle the types of information contained in order flows. This question is becoming increasingly important as the literature has shifted the black box from understanding exchange rate determination to understanding order flow determination.

We build a theoretical model that considers all the information market agents can embed in currency prices. Our modeling approach integrates not solely the public and private information as in previous works (Bachetta and Van Wincoop (2006) and Evans (2010)) but also behavioural components affecting customers and dealers decisions. Our model thus merges two strands of the literature on exchange rates: behavioural exchange rate models and microstructure models of exchange rate. The global model takes account of heterogeneous agents (Frankel and Froot (1986)), the appearance of rumours (Dominguez and Panthaki (2006)), anchoring effects (Kahneman and Tversky (1974), Osler (2002)), status quo bias (Kahneman and Knetsch (1991), De Grauwe and Grimaldi (2008)) and the characteristics of the trading mechanism peculiar to the foreign exchange market (Lyons (1997, 2001)).

4. A theoretical model of the foreign exchange market

4.1 Hypotheses of the model

The model relies on two blocks. The first block is a behavioural model (De Grauwe and Grimaldi (2007)) that provides the characteristics of customers faced by dealers. We assume customers have heterogeneous expectations and are split between two main categories: chartists and fundamentalists. The second block is a microstructure model that represents the trading mechanism of the foreign exchange market. The microstructure model is a simultaneous-trade model that has a decentralised and multiple dealers structure as empirically observed in the foreign exchange market. Our model is based on Lyons (1997,
2001) with added elements from Bachetta and van Wincoop (2006). The microstructure model presents three advantages. First, it considers interdealer trading that accounts for two-thirds of the trades in the foreign exchange market. Secondly, it takes account of customer order flows as the primary source of private information for dealers. Besides, dealers learn about private information from other dealers through the observation of order flows. Thus the model assumes dealers have access to both public and private information. Thirdly, we suppose risk averse dealers as empirically observed in the foreign exchange market. Table 2 summarizes the timing of the model.

<table>
<thead>
<tr>
<th>Time</th>
<th>Agents</th>
<th>Actions</th>
<th>Incoming Information by Type</th>
<th>Main Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time $t$</td>
<td>Customers</td>
<td>Set $\omega_{f,t}$, $\omega_{c,t}$ Trade $OF_t^f$, $OF_t^c$</td>
<td>Models: $(s_t - \bar{F}<em>t)$, $(s</em>{t-2})$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Fundamentals: $i_t$, $i_t^<em>$, $d_t$, $d_t^</em>$, $bc_t$, $bc_t^*$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Market Psychology: $\Psi_t^f$, $\Psi_t^c$</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Unexpected news: $\bar{e}_t$, $\bar{e}_t^f$, $\bar{e}_t^c$</td>
<td>$P_{0,t} = {s_t, \bar{e}_t}$</td>
</tr>
<tr>
<td>Time $t$</td>
<td>Dealers</td>
<td>Quote $p_{1,t}^i$</td>
<td>Public signal: $(i_t - i_t^*)$ through $s_t$, $\bar{e}_t$, $\bar{e}_t^M$</td>
<td>$P_{1,t}^i = {p_{0,t}, p_{1,t}^i}$</td>
</tr>
<tr>
<td>Time $t$</td>
<td>Dealers</td>
<td>Quote $p_{1,t}^i$</td>
<td>Private information: $\bar{e}_t^M$ inferred from order flows ($OF_t^f$, $OF_t^c$)</td>
<td>$P_{1,t}^i = {p_{0,t}, \bar{e}_t^M}$</td>
</tr>
<tr>
<td></td>
<td>Dealers</td>
<td>Trade $T_{1,t}^i$, Receive $T_{1,t}^i$</td>
<td>Public information: ${p_{1,t}^i}<em>{i=1}^{n}$ or $\bar{P}</em>{1,t}$</td>
<td>$T_{1,t} = \bar{P}_{1,t}$</td>
</tr>
<tr>
<td></td>
<td>Dealers</td>
<td>Observe $V_{1,t}$</td>
<td>Public information: $s_t$, $\bar{P}<em>{1,t}$, $V</em>{1,t}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dealers</td>
<td>Quote $p_{2,t}^i$</td>
<td>Public information: $s_t$, $\bar{P}<em>{1,t}$, $V</em>{1,t}$, $\bar{e}_t$</td>
<td>$P_{2,t} = {\bar{P}<em>{1,t}, V</em>{1,t}, \bar{e}_t}$</td>
</tr>
<tr>
<td>Time $t$</td>
<td>Dealers</td>
<td>Trade $T_{2,t}^i$, Receive $T_{2,t}^i$</td>
<td>Public information: $V_{1,t}$, $\bar{P}_{2,t}$</td>
<td>$T_{2,t} = {V_{1,t}, \bar{P}_{2,t}, \bar{e}_t}$</td>
</tr>
<tr>
<td></td>
<td>Dealers</td>
<td>Observe $V_{2,t}$; $F_t$ Realised</td>
<td>Private information: $\bar{e}_t$</td>
<td></td>
</tr>
</tbody>
</table>

The timing of the model is described as follows. First, customers form their expectations based on their stock of information and their proper models of exchange rate determination. At the same time, dealers set their price based on public information. Customers then ask dealers about their listed price and choose their optimal dealer according to the prices set by dealers.

Trades in the microstructure model are split into two periods. In the first period the chosen dealers trade with their customers. Such dealers observe the flows coming from

---

5 Since in the foreign exchange market, the bid/ask spread is low due to a high degree of liquidity, we assume a bid/ask spread equal to zero in our model.
customers and try to infer the private information contained in customer order flows. In the second period, dealers trade among other dealers to adjust their stock of risky asset in two ways; either to satisfy the net demand of their customers or to take positions on currencies.

In our model the price of the currency is affected through two channels: a direct channel and an indirect channel. In the direct channel, the price of the currency can change with the arrival of public news even if there is no trade in the market. In the indirect channel, private information coming from customers affect currency prices through order flows.  

Sections 4.2 and 4.3 describe the structure of the model.

### 4.2 The behavioural model

The behavioural model is based on an heterogeneous agents structure (Frankel and Froot (1986), De Grauwe and Grimaldi (2007)). The model assumes customers can choose between two forecasting rules: a chartist rule and a fundamentalist rule. Fundamentalists forecast exchange rates based on the spread between the current exchange rate \( s_t \) and the fundamental exchange rate \( \bar{s}_t \):

\[
\Delta s^f_{t+1} = - \alpha_1(s_t - \bar{s}_t) + \alpha_2 \Psi^f_t + \epsilon^f_t \quad \text{With } \{ \alpha_1, \alpha_2 \} > 0 \quad (1.1)
\]

Thus if the exchange rate is over-appreciated (under-appreciated) relative to its fundamental value, fundamentalists will expect the currency to depreciate (appreciate). The parameter \( \alpha_1 \) represents the speed at which the exchange rate returns towards its fundamental value. The higher \( \alpha_1 \) the stronger the return force of exchange rates towards their fundamental value. The fundamental exchange rate \( \bar{s}_t \) is determined by the interest rate differential between the two countries \((i_t - i^*_t)\):

\[
\bar{s}_t = (i_t - i^*_t) \quad (1.2)
\]

With \( i_t = i_{t-1} + \epsilon_i \) where \( i_t \to N(0, \sigma_i^2) \) and \( \epsilon_i \to N(0, \sigma_\epsilon^2) \); \( i^*_t = \alpha^* i^*_{t-1} + \epsilon^*_i \) where \( \epsilon^*_i \to N(0, \sigma_{i*}^2) \).

Fundamentalists thus magnify exchange rates movements. The parameter \( \beta_1 \) represents the degree of interpolation. The higher \( \beta_1 \), the larger the influence of past exchange rate dynamics on chartists’ forecasts.

Chartists interpolate past trends of exchange rates dynamics to forecast future currency prices:

\[
\Delta s^c_{t+1} = \beta_1(s_{t-2}) + \beta_2 \Psi^c_t + \epsilon^c_t \quad \text{With } \{ \beta_1, \beta_2 \} > 0 \quad (2)
\]

Thus when the exchange rate has appreciated (depreciated) in the past; chartists expect a further appreciation (depreciation) of the currency. Chartists thus magnify exchange rates movements. The parameter \( \beta_1 \) represents the degree of interpolation. The higher \( \beta_1 \), the larger the influence of past exchange rate dynamics on chartists’ forecasts.

---

6 The distinguishing feature between the two channels is easily understood with an example taken from Evans and Lyons (2008) and Evans (2009).

7 The interest rate differential has been filtered by a Hodrick-Prescott filter because we assume that the dynamics of the fundamental exchange rate are smooth over time.
The parameters $\Psi_f^t$ and $\Psi_c^t$ represent the effects of collective psychology respectively for fundamentalists and chartists. We assume two definitions for this component. First collective psychology is defined by the appearance of rumours (Dominguez and Panthaki (2006)) that counter past trends of the exchange rate:

$$\Psi_{1,t} = \frac{-1}{T} \sum_{i=1}^{T} s_{t-i}$$  \hspace{1cm} (3.1)

Secondly, collective psychology is also materialised by the anchoring effect (Kahneman and Tversky (1974), Osler (2002)). When the exchange rate variation is lower than a constant ($|\Delta s_{t-i}| \leq c$), the exchange rate fluctuates around a threshold value following a stable random walk ($0 < \theta < 1$). Conversely, if the exchange rate variation is higher than a constant then the exchange rate wanders away from its current threshold and reaches a new threshold.

$$\Psi_{2,t} = \left\{ \begin{array}{ll} \theta_{t-i-1} + \varepsilon_t & \text{if } |\Delta s_{t-i}| \leq c \\ \Lambda + \theta_{t-i-1} + \varepsilon_t & \text{if } |\Delta s_{t-i}| > c \end{array} \right. \hspace{1cm} (3.2)$$

With $0 < \theta < 1$ and $\Lambda$, a constant

The transition between the two states is driven by the following function:

$$F = \left( \frac{1}{\theta} \right) s_{t-i} + \varepsilon_t.$$ 

The weight that market agents attribute to a given rule depends on the profitability of a particular rule. The more profitable a rule, the higher the weight agents attach to this rule. Chartist and fundamentalist weights are defined as:

$$\omega_{c,t} = \frac{\exp(\gamma \pi'_{c,t})}{[\exp(\gamma \pi'_{c,t}) + \exp(\gamma \pi'_{f,t})]} \quad \text{and} \quad \omega_{f,t} = \frac{\exp(\gamma \pi'_{f,t})}{[\exp(\gamma \pi'_{c,t}) + \exp(\gamma \pi'_{f,t})]} \hspace{1cm} (4)$$

Where $\omega_{f,t} + \omega_{c,t} = 1$ and $0 < \gamma < 1$

The parameter $\gamma$ represents the intensity at which agents revise their forecasting rules. When $\gamma \to \infty$, agents choose the rule which proves to be the most profitable. Conversely, when $\gamma \to 0$, agents keep the rule they are using and are insensitive to the profitability of this rule. Thus $\gamma$ can be viewed as a representation of the status quo bias in agents’ behaviour. The status quo bias highlighted by Kahneman and Knetsch (1991) means that when agents use a given rule, they find it difficult to change for a different rule. We assume agents need some time to change their rule ($\gamma = 0.2$).

The profitability $\pi'_{i,t}$ of each rule is evaluated according to the profit $\pi_{i,t}$ and the risk $\sigma^2_{i,t}$ associated to a given rule:

$$\pi'_{i,t} = \pi_{i,t} \cdot \mu \sigma^2_{i,t} \quad \text{and} \quad i = c, f \hspace{1cm} (5)$$
The parameter $\mu$ represents the coefficient of risk aversion (we set $\mu = 5$). The risk associated to a forecasting rule is defined as the variance of the forecasting error:

$$\sigma^2_{i,t} = [E_{i,t}(s_i) - s_i]^2 \quad i = c, f$$

(6)

The profit $\pi_{i,t}$ related to a forecasting strategy is defined as the one-period earnings of investing one unit of domestic currency in the foreign asset:

$$\pi_{i,t} = [s_t(1 + r^*) - s_{t-1}(1 + r)]sgn[E_{i,t}(s_t)(1 + r^*) - s_{t-1}(1 + r)] + c_{i,t}f(6)$$

Where

$$\begin{align*}
\text{sgn}[x] &= 1 \text{ if } x > 0 \\
\text{sgn}[x] &= 0 \text{ if } x = 0 \\
\text{sgn}[x] &= -1 \text{ if } x < 0
\end{align*}$$

Thus when agents forecast an appreciation of the foreign currency (an increase in $s_t$) they will invest in the foreign country. If this appreciation is realised then their profit is equal to the appreciation of the foreign currency, adjusted by the interest rate differential. Conversely, if the foreign currency depreciates ($s_t$ decreases) agents will face a loss which equals the depreciation of the foreign currency, adjusted by the interest rate differential.

We assume fundamentals have an influence on exchange rate dynamics in the long run. More precisely, we assume that the external debt exerts a return force on currency prices such that the exchange rate returns towards its equilibrium value in the long run. The dynamics of the domestic (foreign) external debt $d_t$ ($d_t^*$) are defined as:

$$d_t = d_{t-1} + i_t d_{t-1} + bc_t(s_{t-1}) = (1 + i_t)d_{t-1} - \theta(s_{t-1}^{\text{final}})$$

(8.1)

$$d_t^* = d_{t-1}^* + i_t^* d_{t-1}^* + bc_t^*(s_{t-1}) = (1 + i_t^*)d_{t-1}^* + \theta(s_{t-1}^{\text{final}})$$

(8.2)

With $d_t$ ($d_t^*$), the domestic (foreign) external debt; $i_t$ ($i_t^*$), the domestic (foreign) interest rate; $bc_t$ ($bc_t^*$) the domestic (foreign) current account; $s_{t-1}$, the final exchange rate; $\theta = 0,25$; $d_t = d_{t-1} + \varepsilon_t$ where $d_t \sim N(0, \sigma_d^2)$ and $\varepsilon_t \sim N(0, \sigma_e^2)$; $d_t^* = d_{t-1}^* + \varepsilon_t^*$, where $d_t^* \sim N(0, \sigma_d^{\text{std}})$ and $\varepsilon_t^* \sim N(0, \sigma_e^{\text{std}})$ (initially we assume $d_{t-1} = 0$)

The stock of debt at time $t$ is therefore equal to the stock of debt at time $t-1$ ($d_{t-1}$); plus the interest rate bear on the debt ($i_t d_{t-1}$) and the current account balance at time $t$ ($bc_t$). The current account is related to the exchange rate dynamics by an inverse relationship. Thus when the domestic currency appreciates, the current account worsens and vice versa. We assume also that fundamentalists do not take account of the effect of the external debt on the exchange rate in their rule. The external debt has here an external effect on exchange rate dynamics. In other words, the external debt influences the exchange rate dynamics outside the expectations of chartists and fundamentalists.

The expected exchange rate at time $t+1$ is obtained by aggregating agents’ forecasts in the market:
\[ E_t(\Delta s_{t+1}) = \omega_{f,t} E_f(\Delta s_{t+1}) + \omega_{c,t} E_c(\Delta s_{t+1}) - \theta(d_{t-1} - d_{t-1}^*) \]

\[ \iff \quad E_t(\Delta s_{t+1}) = -\omega_{f,t} \psi(s_t - s_t^*) + \omega_{c,t} \beta \Delta s_t - \theta(d_{t-1} - d_{t-1}^*) + e_{Market}^{\text{Market}} \quad (9) \]

With \( \theta = 0.25 \) and initially, \( d_0 = 0 \)

The following rules provide the link between the behavioural model and the microstructure model. Order flows from fundamentalists (\( OF^f_t \)) and chartists (\( OF^c_t \)) are defined as:

\[ OF^f_t = F(\Delta s^f_{t+1}) = N. \Delta s^f_{t+1} \quad \text{where} \quad OF^f_t \in IN \quad \text{and} \quad \begin{cases} OF^f_t > 0 & \Delta s^f_{t+1} > 0 \\ OF^f_t = 0 & \Delta s^f_{t+1} = 0 \\ OF^f_t < 0 & \Delta s^f_{t+1} < 0 \end{cases} \quad (10) \]

\[ OF^c_t = F(\Delta s^c_{t+1}) = N. \Delta s^c_{t+1} \quad \text{where} \quad OF^c_t \in IN \quad \text{and} \quad \begin{cases} OF^c_t > 0 & \Delta s^c_{t+1} > 0 \\ OF^c_t = 0 & \Delta s^c_{t+1} = 0 \\ OF^c_t < 0 & \Delta s^c_{t+1} < 0 \end{cases} \quad (11) \]

Therefore, when customers expect an appreciation of the currency, they will buy the currency. Conversely, when customers expect a depreciation of the currency, they will sell the currency. We assume customers select an optimal dealer. Customers willing to buy the risky asset choose the dealer that quotes the minimum price. Conversely, customers willing to sell the risky asset choose the dealer that quotes the maximum price. The total amount of customer order flows at time \( t \) is given by:

\[ OF_{t \text{ customers}} = \omega_t OF^f_t + (1 - \omega_t) OF^c_t \quad \text{(12)} \]

Table 3 decomposes the various types of information of the behavioural model.

**Table 3: Decomposition of the information contained in the behavioural model**

<table>
<thead>
<tr>
<th>Information Type</th>
<th>Public Fundamental Information</th>
<th>Public Psychological Information</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fundamentalist Rule</strong></td>
<td>( s_t, \bar{s}_t, i_t, i_t^<em>, d_t, d_t^</em>, bc_t, bc_t^* )</td>
<td>( \Psi^f_t )</td>
<td>( e^f_t )</td>
</tr>
<tr>
<td><strong>Chartist Rule</strong></td>
<td>( s_{t-2} )</td>
<td>( \Psi^c_t )</td>
<td>( e^c_t )</td>
</tr>
<tr>
<td><strong>Private Fundamental Information</strong></td>
<td>( \alpha_t(s_t - \bar{s}_t) )</td>
<td>( \alpha^2 \Psi^f_t )</td>
<td>( e^f_t )</td>
</tr>
<tr>
<td><strong>Private Psychological Information</strong></td>
<td>( \beta_t(s_{t-2}) )</td>
<td>( \beta_t \Psi^c_t )</td>
<td>( e^c_t )</td>
</tr>
</tbody>
</table>
The behavioural model contains four types of information: public fundamental information, private fundamental information, public psychological information and private psychological information.

Public fundamental information \((s_t, \bar{s}_t, i_t, i_t^*, d_t, d_t^*, bc_t, bc_t^*)\) deals with information concerning macroeconomic fundamentals. Every agent has access to public fundamental information.

Private fundamental information regroups information about fundamentals that has been analysed or processed by agents. The terms \(\alpha_i(s_t - \bar{s}_t)\) and \(\beta_i(s_{t-2})\) describe the model of exchange rate determination in which agents believe. They are related to the internal psychology of agents.

Public psychological information \((\Psi_t^f, \Psi_t^c)\) relates to information about market psychology (or market agents behaviours) that can be observed by every agent. This type of information is associated to the external psychology of agents and can be illustrated by the anchoring effects or incoming rumours.

Private psychological information \((\alpha_t^2, \Psi_t^f, \beta_t^2, \Psi_t^c)\) defines the weight attributed by customers to the psychological component of exchange rate. Intuitively, this weight defines the degree of rationality of agents. Agents with no psychological components will be considered as more rational than agents who attribute a high weight to this component.

The parameter \(\varepsilon_t^f(\varepsilon_t^c)\) is a white noise that represents unexpected news or unexpected behaviours of fundamentalists (chartists). Therefore, the noise parameters can represent either public information or private information about fundamental or customers’ behaviours.

4.3 The microstructure model

We follow Lyons (1997) and model the trading mechanism of the foreign exchange market with a simultaneous-trade model with multiple dealers. We assume the existence of \(n\) dealers in the market. In this model, dealers are not solely market-makers (they match the supply and demand of currencies); they are also speculators (they take positions on currencies).

4.3.1 Period 1 of the microstructure model

Given their information set (public and private signal), dealers set their currency price based on the following rule:

\[
P_{0,t}^i = s_t + \xi_{0,t}^i + \varepsilon_{t,Market}^i
\]

Where \(\xi_{0,t}^i \sim iidN(\mu;\sigma_\xi)\) and \(\varepsilon_{t,Market}^i \sim iidN(\mu;\sigma_\varepsilon)\)

The first price \(P_{0,t}^i\) set by dealers includes public information about fundamentals \(s_t\), private information proper to the dealer \(\xi_{0,t}^i\) and unexpected news about fundamentals \(\varepsilon_{t,Market}^i\). \(\xi_{0,t}^i\) is interpreted as a private signal that dealers held concerning the future exchange rate dynamics. This private signal induces a difference among prices listed by dealers.
Equation (13) is the start of the direct channel of news incorporation into currency prices. Indeed, the price of the currency can change with the arrival of public news (through the terms $\varepsilon_{t,Market}$) even if there is no trade in the market ($OF_{t,customers} = 0$).

Once dealers set their price, customers select their optimal dealers. Customers willing to buy the risky asset will choose the dealer that quotes the minimum price. Conversely, customers willing to sell the risky asset will choose the dealer that quotes the maximum price.

If $OF_{t}^{f} > 0$, fundamentalists trade with dealer $i$ such that:

$$P_{0}^{i} = \text{Min}\{P_{0}\} \quad \forall i \in n$$

$$P_{0}^{i} = \text{Max}\{P_{0}\} \quad \forall i \in n$$

If $OF_{t}^{c} > 0$, chartists trade with dealer $i$ such that:

$$P_{0}^{i} = \text{Min}\{P_{0}\} \quad \forall i \in n$$

$$P_{0}^{i} = \text{Max}\{P_{0}\} \quad \forall i \in n$$

(14)

Notice that some dealers receive orders from customers while other dealers do not. We thus face two cases. On the one hand, dealers that receive orders from customers have access to private information and include it into their price. On the other hand, dealers that do not receive any orders from customers do not have access to private information. Such dealers will learn about private information through the hot potato effect i.e. through interdealers order flows in period 2. Therefore customer order flow is the source of information asymmetry in this model. Thus private information will be reflected into prices only if it is not reflected in customer order flows and in interdealer order flows.

When dealers receive the information from customers, they will try to infer the private information contained in order flows. If dealers receive positive (negative) customer order flows $OF_{t}^{f} + OF_{t}^{c} > 0$ ($OF_{t}^{f} + OF_{t}^{c} < 0$), they will include a positive (negative) private signal $\xi_{i,t}^{f}$ ($\xi_{i,t}^{c}$) in their quoted price $P_{0}^{i}$. If dealers receive no customer order flows ($OF_{t}^{f} = OF_{t}^{c} = 0$), they receive no private signal from customers. We assume that the signal $\xi_{i,t}$ extracted by dealers from customer order flows follows a white noise process. The quoted price $P_{0}^{i}$ by dealers after trades with customers is thus given by:

$$P_{0}^{i} = P_{0}^{i} + \begin{cases} 
\xi_{i,t}^{f} & \text{if } OF_{t}^{f} + OF_{t}^{c} > 0 \\
\xi_{i,t}^{c} & \text{if } OF_{t}^{f} + OF_{t}^{c} < 0 \\
0 & \text{if } OF_{t}^{f} + OF_{t}^{c} = 0
\end{cases}
$$

Where $\xi_{i,t}^{f} \sim iidN(\mu,\sigma_{\xi})$ and $\xi_{i,t}^{c} \sim iidN(\mu,\sigma_{\xi})$ (15)

Dealers quote their price simultaneously and independently. Quoted price are observable and available to all dealers. Each quote is a single price at which the dealer agrees both to buy and sell. Equation (15) is the start of the indirect channel in which dispersed or private information coming from customers affect currency prices through order flows, based on the term $\xi_{i,t}$.

We define the demand for the risky asset by dealers or the desired stock of currency in period 1 for dealer $i$ $D_{i,t}$ by:
\[ D_{1,t} = a_1 s_t + a_2 \xi_{0,t} + a_3 \xi_{1,t} - a_4 \Omega_{1,t} \]  

(16)

With \( a_3 = \frac{\gamma_i}{\mu_d} \), \( 0 < \{a_1, a_2, a_4\} < 1 \) and \( \Omega_{1,t} = \frac{1}{N} \sum_{i=1}^{N} P_{1,t} \)

Therefore dealers have access to both public and private information sources. Their demand for the risky asset depends on public information \( s_t \) (the higher \( s_t \), the more appreciated the value of the stock of risky asset; the higher the demand for the risky asset); private information coming from customer order flows \( \xi_{1,t} \) (the higher \( \xi_{1,t} \), the higher the incentive for dealers to invest in the risky asset); the private signal that dealers held on the future exchange rate dynamics \( \xi_{0,t} \) (the higher \( \xi_{0,t} \), the higher the incentive for dealers to invest in the risky asset); and the average price set by dealers in period 1 \( \Omega_{1,t} \) (the higher the price of the risky asset, the lower the demand for the risky asset).

Dealers are also speculators in this model. They benefit from the information contained in the received customer orders to take speculative positions. The term \( \gamma_d \) takes account of the speculative dimension of dealers. This term acts as a leverage effect on the demand for currencies by dealers. We assume that the willingness to buy or sell currencies for dealers depends on the amount bought or sold by their customers. If dealers receive customer orders higher than the average order flows received in the past from customers, they will buy a higher amount of currencies. Conversely, if dealers receive customer orders lower than the average order flows received in the past from customers, they will buy a lower amount of currencies. The same reasoning holds when selling currencies. Thus, the willingness to buy/sell currencies by dealer \( i \) is defined by the term \( \gamma_i \) such as:

\[
\gamma_i^i = \begin{cases} 
0 < \gamma_i^i < 1 & \text{if } OF_{i, \text{customer}}^\text{customer} < OF_{i}^\text{customer} \\
\gamma_i^i > 1 & \text{if } OF_{i, \text{customer}}^\text{customer} > OF_{i}^\text{customer}
\end{cases}
\]  

(17)

The parameter \( \mu_d \) represents the degree of risk aversion of dealers: if \( \mu_d < 1 \), dealers are risk lover; if \( \mu_d > 1 \), dealers are risk averse; if \( \mu_d = 1 \), dealers are risk neutral.

Beyond their role of speculators, dealers are also market-makers. They match the demand and supply of currencies by customers. We define the dealer \( i \) trading rule \( T_{1,t} \) in period 1 as:

\[ T_{1,t} = D_{1,t} + C_{1,t} + E[T_{1,t}^\text{customer} / \Omega_{1,t}^\text{customer}] \]  

(18)

The term \( T_{1,t} \) depends on \( D_{1,t} \), \( C_{1,t} \) and \( E[T_{1,t}^\text{customer} / \Omega_{1,t}^\text{customer}] \). Assume initially that the stock of risky assets for dealers is equal to zero. The term \( T_{1,t} \) is the necessary amount of orders that dealers have to pass to other dealers to satisfy their own demand of risky asset given orders coming from customers and orders from other dealers. The term \( C_{1,t} \) represents customer order flows addressed to dealer \( i \). Customers will be net buyers if \( C_{1,t} > 0 \). Conversely, customers will be net sellers if \( C_{1,t} < 0 \). Obviously, \( C_{1,t} = OF_{i,t}^\text{customer} + OF_{i, \text{customer}}^\text{customer} \). If the dealer does not receive any orders from customers, then \( OF_{i,t}^\text{customer} = OF_{i, \text{customer}}^\text{customer} = 0 \) and \( C_{1,t} = 0 \). As dealers’ trades are simultaneous, \( E[T_{1,t}^\text{customer} / \Omega_{1,t}^\text{customer}] \) represents the order flows from other dealers expected by dealer \( i \). We define
\[ E[T_i^j / \Omega_i^j] \text{ as: } E[T_i^j / \Omega_i^j] = T_{2,j-1}^i + \varepsilon_i^j. \]

The term \( T_{2,j-1}^i \) represents the net flows received by dealer \( i \) from other dealers in period 2. The term \( D_i^j \) is the desired stock of currencies by dealer \( i \).

The definition of order flows by dealer \( i \) in period 1 is given by:

\[ T_i^j = D_i^j + C_i^j + E[T_i^j / \Omega_i^j] \quad (19) \]

Dealers then choose to trade with their optimal dealers. Buyer dealers will buy currencies at the lowest price. Seller dealers will sell currencies at the highest price:

\[
\begin{cases}
T_i^j > 0 & \text{the dealer } i \text{ trades with dealer } j \text{ such as: } P_i^j = \min\left\{ P_j^i \right\} \forall j \in n \\
T_i^j < 0 & \text{the dealer } i \text{ trades with dealer } j \text{ such as: } P_i^j = \max\left\{ P_j^i \right\} \forall j \in n
\end{cases}
\]

(21)

The net cumulated interdealer order flows in period 1 amount to:

\[ V_j = \sum_{i=1}^{n} T_i^j \quad (22) \]

### 4.3.2 Period 2 of the microstructure model

In period 2, dealers trade between each other. Their trades are based on private information contained in order flows. Dealers start to revise their quoted price given their updated stock of information. We assume that the price quoted by dealers in period 2 is linked to the latest market quote \( P_j^i \) and to the net interdealer order flows in period 1 \( V_j \). This assumption gives more stability to the model. Hence:

\[ P_{2,j}^i = \frac{\varepsilon_j^i}{\mu_i} \begin{cases} V_j > 0 & \text{if } \varepsilon_{2,j}^i \in [0,1] \\
0 & V_j = 0 \end{cases} \]

(23)

Once dealers have set their price in period 2, they define their net demand for currencies in period 2 \( D_{2,j}^i \) according to the following relationship:

\[ D_{2,j}^i = \frac{1}{\mu_d} \left( b_1 s_i + b_2 V_j - b_3 P_{1,j}^i \right) + \frac{\gamma_j^i}{\mu_d} \varepsilon_{3,j}^i \]

(24)

With \( P_{2,j}^i = \frac{1}{N} \sum_{i=1}^{n} P_i^j \), \( 0 < \{b_1, b_2, b_3\} < 1 \) and \( b_1 > b_3 \)

---

8 Initially, we set \( T_{2,j-1}^i = 0 \) and \( E[T_i^j / \Omega_i^j] = \varepsilon_i^j \).

9 As in Lyons (1997), we assume that the initial demands of dealers are equal to zero.
And \( \xi_{3,t}^{i} = \begin{cases} \xi_{3,t}^{i} & T_{1,t}^{i} < \bar{T}_{1,t}^{i} \\ \xi_{3,t}^{i} & \text{if } T_{1,t}^{i} > \bar{T}_{1,t}^{i} \\ 0 & T_{1,t}^{i} = \bar{T}_{1,t}^{i} \end{cases} \) where \( \xi_{3,t}^{i} \sim iidN(\mu, \sigma) \) and \( \xi_{3,t}^{i} \in [0, 1] \) \( \xi_{3,t}^{i} \sim iidN(\mu, \sigma) \) and \( \xi_{3,t}^{i} \in [-1, 0] \) (25)

Hence the demand for currencies in period 2 \( D_{2,t}^{i} \) depends on public information \( s_{t} \) (the higher \( s_{t} \), the more appreciated the value of the stock of risky asset, the higher the demand for the risky asset); interdealer order flows \( V_{1,t} \) observed by dealers at the end of period 1 (the more positive \( V_{1,t} \), the more appreciated the value of the stock of risky asset, the higher the demand for the risky asset); the average price set by dealers in period 2 \( \bar{T}_{2,t}^{i} \) (the higher the price of the risky asset, the lower the demand for the risky asset); private information coming from dealers that received customer order flows in period 1 \( \xi_{3,t}^{i} \) (the higher \( \xi_{3,t}^{i} \), the higher the incentive for dealers to invest in the risky asset). Indeed, in period 2, dealers infer private information \( \xi_{3,t}^{i} \) from customer order flows through order flows coming from dealers that had traded with customers in period 1. Recall that the only way dealers can learn about private information from other dealers is through the observation of interdealer order flows.

Dealers are also speculators. The term \( \gamma_{2}^{i} \) takes account of the speculative dimension of dealers. This term acts as a leverage effect on the demand for currencies by dealers. We assume the willingness to buy or sell the risky asset for a dealer depends on the amount bought or sold by their dealers’ counterparts. Therefore, if a dealer receives orders higher than the average flows received in the past, he will buy a higher amount of risky asset. Conversely, if a dealer receives orders lower than the average flows received in the past; he will buy a lower amount of risky asset. The same reasoning holds when selling currencies. The term \( \gamma_{2}^{i} \) defines the willingness to buy/sell the risky asset:

\[
\gamma_{2}^{i} = \begin{cases} 0 < \gamma_{2}^{i} < 1 & \text{if } T_{1,t}^{i} < \bar{T}_{1,t}^{i} \\ \gamma_{2}^{i} > 1 & \text{if } T_{1,t}^{i} > \bar{T}_{1,t}^{i} \end{cases}
\]

(26)

The parameter \( \mu_{d} \) represents the degree of risk aversion of dealers: if \( \mu_{d} < 1 \), dealers are risk lover; if \( \mu_{d} > 1 \), dealers are risk averse; if \( \mu_{d} = 1 \), dealers are risk neutral.

The dealer trading rule in period 2 is defined as follows:

\[
T_{2,t}^{i} = D_{2,t}^{i} - D_{1,t}^{i} + T_{1,t}^{i} - E[T_{1,t}^{i} / \Omega_{1,t}^{i}] + E[T_{2,t}^{i} / \Omega_{2,t}^{i}]
\]

(27)

The term \( T_{2,t}^{i} \) depends on \( D_{1,t}^{i}, D_{1,t}^{i}, T_{1,t}^{i}, E[T_{1,t}^{i} / \Omega_{1,t}^{i}] \) and \( E[T_{2,t}^{i} / \Omega_{2,t}^{i}] \). The flows \(( D_{2,t}^{i} - D_{1,t}^{i} )\) represent a revision by dealer \( i \) of the amount invested in currencies. The term \(( D_{2,t}^{i} - D_{1,t}^{i} )\) is interpreted as an inventory effect. The inventory effect in turn triggers the hot potato effect. Hence agents pass their undesired positions to other dealers in the market through the term \( T_{2,t}^{i} \). Trades in period 2 depend also on the error made by a dealer on the expected flows coming from other dealers \( (T_{1,t}^{i} - E[T_{1,t}^{i} / \Omega_{1,t}^{i}])^{10} \) in period 1 and on the expected flows coming from other dealers \( (T_{1,t}^{i} - E[T_{1,t}^{i} / \Omega_{1,t}^{i}])^{10} \) in period 1.
order flows to be received in period 2 \( (E[T^i_2 / \Omega^i_2]) \). The expected flows from other dealers by a dealer \( i \) is simply equal to flows received by a dealer \( i \) in period 1, plus a noise:

\[
E[T^i_2 / \Omega^i_2] = \sum_{j=1}^{3} T^i_{1,j} + \varepsilon^i_j \quad \text{With } \varepsilon^i_j \overset{iid}{\sim} N(\mu;\sigma_\varepsilon) \quad (28)
\]

Therefore, the definition of order flows by a dealer \( i \) in period 2 \( T^i_2 \) is given by:

\[
T^i_2 = \frac{1}{\mu_d} (b_1s^i_r + b_2V^i_r - b_3P^i_1) + \frac{\mu_d^i}{\mu_d} \varepsilon^i_j - (T^i_{2,1} + \varepsilon^i_j) + (\sum_{j=1}^{3} T^i_{1,j} + \varepsilon^i_j) \quad (29)
\]

Dealers then choose to trade with their optimal dealer. Buyer dealers will buy currencies at the lowest price. Seller dealers will sell currencies at the highest price:

\[
\begin{align*}
\text{If } \begin{cases} T^i_2 > 0 \end{cases} & \text{ the dealer } i \text{ trade with dealer } j \text{ such as:} \\
\text{If } \begin{cases} T^i_2 < 0 \end{cases} & \text{ the dealer } j \text{ and } i \text{ trade with dealer } j \text{ such as:}
\end{align*}
\]

\[
\begin{align*}
P^i_j &= \text{Min}\{P^i_{2,j}\} \quad \forall j \in n, i \neq j \\
P^i_j &= \text{Max}\{P^i_{2,j}\} \quad \forall j \in n, i \neq j
\end{align*}
\]

The net cumulated interdealer order flows in period 2 amount to:

\[
V^i_{2,t} = \sum_{i=1}^{n} T^i_2 
\]

The final value \( F_t \) of the risky asset in period 2 is given by:

\[
F_t = \frac{1}{n} \sum_{i=1}^{n} P^i_2 = s_{t+1} \quad (32)
\]

### 4.4 Stochastic simulations of the model

We simulate the model over 3000 periods with 50 dealers in the market\(^{11}\). Figure 1.1 shows the dynamics of the simulated exchange rate, the fundamental exchange rate and the proportion of fundamentalists in the market. Figure 1.2 show the relative profitability of the chartists and the fundamentalist rules and the proportion of fundamentalists.

\(^{11}\) The values for the exogenous parameters are available in Appendix F, table F.
From figure 1.1, we observe that in the short run, there is a persistent gap between the simulated exchange rate \( F \) and its fundamental value \( \bar{s} \). Over the long run, the simulated exchange rate returns towards its fundamental value. The heterogeneity of behaviours in the market or equivalently the use of different models by agents explains the disconnection of the market exchange rate from its fundamental value. When chartists dominate the market (white margins), the exchange rate wanders away from its fundamental value. Conversely, when fundamentalists dominate the market (blue margins), the exchange rate returns towards its fundamental value.

As shown in figure 1.2 the domination of a given type of agent in the market depends on the profitability of its proper rule. If the profitability of the chartist rule is higher than the profitability of the fundamentalist rule, chartists dominate the market. Conversely, when the fundamentalist rule becomes more profitable than the chartist rule, fundamentalists dominate the market.

Figure 2.1 and 2.2 shows the dynamics of the simulated exchange rate with respectively the ones of customer order flows and interdealer order flows.
From figures 1.1, 2.1 and 2.2, we observe that the model replicates three stylised facts observed empirically in the foreign exchange market.

First of all, simulations in figures 2.1 and 2.2 confirm the close link between exchange rate dynamics and cumulative order flows at short and long horizons. The coefficient of correlation between the simulated exchange rate and customer order flows (interdealer order flows) amounts to 99.47% (respectively 98.42%). This result comes in line with the empirical observations by microstructure theorists (Lyons (2001), Evans and Lyons (2001, 2002a, 2002b), Rime et al. (2010) to cite a few).

Secondly, the amount of interdealer order flows is larger than the amount of customer order flows. This fact is due to the hot potato effect. This phenomenon describes the fact that with the incoming stock of new information dealers revise their demands of currencies. Revisions in their willing stock of currencies induce inventory imbalances or undesired stock of currencies. Dealers get rid of these inventory imbalances by passing them to other dealers. As a result, inventory imbalances are passed from dealers to dealers in the market. These trades of unwanted positions inflate the amount of flows between dealers in the market. These trades further magnify the amount of interdealer order flows relative to the initial amount of customer order flows. In the model, the hot potato effect appears in period 2 where dealers trade between each other. The hot potato effect is defined through the term \( T_2^i \) by the inventory effect or equivalently the revision of undesired positions on currencies \( (D_i^j - D_i^i) \). Such inventory effects are an important feature of models willing to address trading mechanism in the foreign exchange market. Indeed, empirically, the hot-potato effect represents 60% of the trades between agents in the foreign exchange market (Lyons (2001)).

Thirdly, figures 1.1, 2.1 and 2.2 show that in the short run, the simulated exchange rate is disconnected from its fundamentals but not from order flows. However, in the long run, the dynamics of the simulated exchange rate returns towards its fundamental value and is still highly correlated with order flows. This result comes in lines with the one from the theoretical work by Bachetta and van Wincoop (2006) and the empirical work by Berger et al. (2008).
5. Further results from the theoretical model of the foreign exchange market

5.1 Is the foreign exchange market intrinsically inefficient?

According to Fama (1965), a market is considered as informationally efficient if the price of an asset is equal to its fundamental value, given all available information at time $t$. In our theoretical model, we define the fundamental value of the exchange rate $\bar{s}$ by the interest rate differential between the domestic and the foreign country:

$$\bar{s}_t = (i_t - i^*_t)$$

Figure 3 shows the dynamics of the market exchange rate $s^{\text{market}}$, the fundamental exchange rate $\bar{s}$ and the simulated exchange rate $F$ or equivalently the final listed exchange rate.

Figure 3: Market exchange rate ($s^{\text{market}}$), fundamental exchange rate ($\bar{s}$) and simulated exchange rate ($F$)

The market exchange rate $s^{\text{market}}$ (which we could label as the behavioural exchange rate) fluctuates around its fundamental value $\bar{s}$. In some periods, it wanders away while returning to its fundamental value at other periods. The final exchange rate quoted by dealers $F$ (which we could label as the microstructure exchange rate) appears even more disconnected from the fundamental value than the market exchange rate $s^{\text{market}}$.

Therefore, the final price quoted in the foreign exchange market $F$ does not reflect the fundamental value $\bar{s}$ of the asset. The behavioural exchange rate and the microstructure exchange rate are different from the fundamental exchange rate. Thus the foreign exchange market can be considered as intrinsically inefficient: the final quoted value of the exchange rate will never be equal to the fundamental exchange rate. Indeed, the original information that determines the fundamental exchange rate is distorted through agents’ behaviours and
through the quotation process of the final currency price $F$. This information distortion appears at two levels in the model.

On the one hand, information is distorted by the fact that agents have heterogeneous expectations in the market. We label this distortion of information as the behavioural noise. The behavioural noise or behavioural component of the final exchange rate $F$ can be split in two factors: internal factors and external factors.

Internal factors represent individual psychology (or psychological factors observable at agents’ level). Such factors include individual preferences (risk aversion, proper interpretation of news, overreaction to news, learning effects, etc.) but also the specific rules used by individuals (heuristics, heterogeneous expectations, technical models, fundamental models, etc.). For example, in our model, internal factors are represented by agents’ heterogeneous expectations or agents’ heterogeneous models (chartist and fundamentalist rules).

External factors represent global psychology (or psychological factors observable at a global level in the market). They include rumours, mimetism and conventions that influence the market. In the model, external factors are considered through the appearance of rumours (equation (3.1) and also through the anchoring effect (equation (3.2)).

Internal and external psychological factors represent the behavioural biases from the rational expectation hypothesis (such as anchoring biases, overreaction, etc.). Indeed, REH models assume the existence of a representative agent that has homogenous expectations and that is bereft of any psychological dimension.

On the other hand, information is also distorted by the trading mechanism peculiar to the foreign exchange market. This point was already highlighted by Lyons (1998). We label this information distortion as the microstructure noise. The microstructure noise or microstructure component of the final exchange rate $F$ is induced by two factors: the noise brought by the interpretation of private information by dealers and also the noise brought by the passing of undesired positions.

The noise brought by the interpretation of private information by dealers is illustrated as follows. Recall that only a minority of dealers have access to private information. Assume that private information from customers comes to a dealer that offers the optimal price for customers. Then the chosen dealer has to infer the information contained in order flows coming from customers. The dealer provides a more or less correct interpretation of the original private information contained in customer order flows. The dealer’s interpretation of the information is shaped notably by his/her risk aversion and also by his/her desired leverage effect$^{12}$. The dealer will then transmit his/her interpretation of the original private information to another dealer through interdealer order flows. This other dealer will in turn provide a more or less correct interpretation of the information contained in the order flows coming from the first dealer (and hence a more or less correct interpretation of the original private information from the original customer). As a result, if the original private information passes through a large amount of dealers - or equivalently if the hot potato effect is large - then the precision of the original private information is lowered. The final price will be therefore less revealing of the original private information. Hence, the larger the hot potato effect, the higher the information distortion, the lower the efficiency of the foreign exchange market.

The noise brought by the passing of undesired positions works as follows. Recall that independently of the private information received from customers, dealers adjust also their desired positions in the risky asset given their updated stock of information. Although the

---

$^{12}$ Hence the strategic or speculative behaviour of the dealer contributes to the distortion of the original information.
passing of unwanted positions have a transitory effect on the price of the currency, they act as a noise in interdealer order flows. Indeed, dealers do not know whether order flows coming from other dealers define simply unwanted position bereft of any private information from customers or if such order flows coming from other dealers contain any elements of private information. Hence the passing of unwanted positions act as a noise in the extraction of private information from customer order flows. As a result, the larger the amount of unwanted positions in the market (or equivalently the larger the hot potato), the higher the noise in interdealer order flows, the larger the difficulty to extract the original private information provided by customers. Therefore the hot-potato effect - trading mechanism intrinsic to the foreign exchange market - distorts the original private information provided by customers in the final currency price and hence alters the efficiency of the foreign exchange market.

As a consequence, the conjunction of behavioural noise (internal factors and external factors) and microstructure noise (either the interpretation of the private information by dealers or the noise brought by the passing of undesired positions) imply that the foreign exchange market is intrinsically inefficient. The incoming information is distorted by agents’ behaviours and by the trading mechanism peculiar to the foreign exchange market.

5.2 Towards a resolution of the exchange rate disconnection puzzle?

The exchange rate disconnection puzzle states that the empirical dynamics of currency prices are disconnected from their fundamentals. The disconnection puzzle was highlighted by Meese and Rogoff (1983). They found that traditional exchange rate models based on a linear and symmetric structure offer little explanatory and predictive powers concerning exchange rate dynamics, especially in the short run.

We mentioned previously that the explanatory power of exchange rate dynamics by order flows models far exceeds the one of traditional exchange rate models, especially at short horizons. As a result, one may wonder whether order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle?

We analyse the fit of order flows versus fundamentals by relying on the simulated series from our theoretical model of the foreign exchange market. The simulated exchange rate $F$ is the endogenous variable. We consider as exogenous variables the interest rate differential $(i_t - \bar{i}_t)$ that defines the fundamental exchange rate ($\bar{s}$ in the theoretical model) and interdealer cumulated order flows $X_t$ ($V2$ in the theoretical model). All series are non-stationary in level but stationary in first difference within the 3000 periods of simulations (see Appendix E for stationarity tests). Regressions are based on OLS (with Newey-West correction for heteroskedasticity and autocorrelation). Table 4 shows the output.
Table 4: Empirical tests based on simulated series from the theoretical model of the foreign exchange market

<table>
<thead>
<tr>
<th>Model</th>
<th>$\Delta s_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta X_t + \epsilon_t$</th>
<th>Diagnostic Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
<td>LM</td>
</tr>
<tr>
<td></td>
<td>$\beta_0$</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td>Model 1</td>
<td>$\Delta F$</td>
<td>$\beta_2$</td>
</tr>
<tr>
<td></td>
<td>$-7.24 \times 10^{-2}$</td>
<td>$-2.15 \times 10^{-2}$</td>
</tr>
<tr>
<td></td>
<td>[0.60]</td>
<td>[0.99]</td>
</tr>
<tr>
<td></td>
<td>$2.47 \times 10^{-5}$</td>
<td>[41.38]</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>$LM$</td>
</tr>
<tr>
<td></td>
<td>0.60</td>
<td>$ARCH$</td>
</tr>
<tr>
<td></td>
<td>$466.29$</td>
<td>$J&amp;B$</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$339.59$</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$42.54$</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Model 2</td>
<td>$\Delta s_t = \beta_0 + \beta_1 \Delta X_t + \epsilon_t$</td>
<td>LM</td>
</tr>
<tr>
<td></td>
<td>Coefficients</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td></td>
<td>$\beta_0$</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td></td>
<td>$-5.28 \times 10^{-2}$</td>
<td>$2.48 \times 10^{-5}$</td>
</tr>
<tr>
<td></td>
<td>[-0.44]</td>
<td>[41.02]</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>$LM$</td>
</tr>
<tr>
<td></td>
<td>0.59</td>
<td>$ARCH$</td>
</tr>
<tr>
<td></td>
<td>$464.63$</td>
<td>$J&amp;B$</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$332.34$</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$45.01$</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Model 3</td>
<td>$\Delta s_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \epsilon_t$</td>
<td>LM</td>
</tr>
<tr>
<td></td>
<td>Coefficients</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td></td>
<td>$\beta_0$</td>
<td>$\beta_1$</td>
</tr>
<tr>
<td></td>
<td>$-2.97 \times 10^{-7}$</td>
<td>$-9.15 \times 10^{-7}$</td>
</tr>
<tr>
<td></td>
<td>[-1.00]</td>
<td>[-1.63]</td>
</tr>
<tr>
<td></td>
<td>$R^2$</td>
<td>$LM$</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>$ARCH$</td>
</tr>
<tr>
<td></td>
<td>$257.42$</td>
<td>$J&amp;B$</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$297.25$</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>$27.62$</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; p-values are mentioned in brackets; critical values for the test of Student amounts to 1.96 at a 5% confidence level and at 1.64 at a 10% confidence level.

As expected, table 4 shows that order flows provide a better explanatory power of currency movements than fundamentals. Order flows explain a significant part of the variance of exchange rate dynamics considered in first difference ($R^2$ is almost at 60%) contrary to fundamentals ($R^2$ is lower than 1%).

We compare this theoretical result to the empirical fit of order flows models versus traditional models of exchange rate. We rely on the original dataset provided by Evans and Lyons (2002). Tests are based on the deutschemark/dollar, yen/dollar and pound/dollar at a daily frequency, from the 1st May 1996 to the 23rd August 1996. Order flows considered here are interdealer order flows. Because of non-stationarity, series are considered in first difference. Equations are estimated by OLS (with Newey-West correction for heteroskedasticity and autocorrelation). Table 5 shows the output of the regressions.

---

13 We ask every distributor entity of order flows but we did not manage to have access to order flow data. The main reason provided by our contacts was that order flows are confidential data.
Table 5: Empirical tests on the original model of Evans and Lyons (2001, 2002)

<table>
<thead>
<tr>
<th>Model 1</th>
<th>$\Delta s_t = \beta_0 + \beta_1 (i_t - i^*_t) + \beta_2 \Delta X_t + \epsilon_t$</th>
<th>Diagnostic Tests</th>
<th>Coefficients $\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>R2</th>
<th>LM</th>
<th>ARCH</th>
<th>J&amp;B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-3.55x10^{-4} [-1.67]</td>
<td>9.45x10^{-1} [1.23]</td>
<td>2.24x10^{-4} [0.17]</td>
<td>0.65</td>
<td>1.35 (0.50)</td>
<td>6.69 (0.03)</td>
<td>7.45 (0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>9.30x10^{-4} [3.20]</td>
<td>3.69x10^{-1} [0.49]</td>
<td>3.82x10^{-4} [6.67]</td>
<td>0.37</td>
<td>7.31 (0.02)</td>
<td>3.50 (0.17)</td>
<td>7.67 (0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-4.44x10^{-4} [-1.29]</td>
<td>3.13x10^{-1} [0.26]</td>
<td>2.83x10^{-4} [8.73]</td>
<td>0.46</td>
<td>3.40 (0.18)</td>
<td>5.51 (0.06)</td>
<td>0.28 (0.87)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2</th>
<th>$\Delta s_t = \beta_0 + \beta_1 \Delta X_t + \epsilon_t$</th>
<th>Diagnostic Tests</th>
<th>Coefficients $\beta_0$</th>
<th>$\beta_1$</th>
<th>R2</th>
<th>LM</th>
<th>ARCH</th>
<th>J&amp;B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-3.82x10^{-4} [-1.73]</td>
<td>2.31x10^{-4} [10.59]</td>
<td>0.63</td>
<td>0.95 (0.61)</td>
<td>5.78 (0.05)</td>
<td>2.73 (0.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-5.64x10^{-4} [1.61]</td>
<td>2.71x10^{-4} [2.92]</td>
<td>0.18</td>
<td>9.72 (0.00)</td>
<td>0.65 (0.72)</td>
<td>8.35 (0.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-4.40x10^{-4} [-0.79]</td>
<td>2.65x10^{-4} [5.48]</td>
<td>0.43</td>
<td>5.26 (0.07)</td>
<td>0.72 (0.69)</td>
<td>0.89 (0.63)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 3</th>
<th>$\Delta s_t = \beta_0 + \beta_1 (i_t - i^*_t) + \epsilon_t$</th>
<th>Diagnostic Tests</th>
<th>Coefficients $\beta_0$</th>
<th>$\beta_1$</th>
<th>R2</th>
<th>LM</th>
<th>ARCH</th>
<th>J&amp;B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-4.46x10^{-4} [-1.08]</td>
<td>3.02x10^{-4} [2.15]</td>
<td>0.05</td>
<td>0.23 (0.88)</td>
<td>0.30 (0.85)</td>
<td>63.52 (0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-4.72x10^{-4} [1.19]</td>
<td>-1.34x10^{-4} [-0.21]</td>
<td>0.00</td>
<td>2.38 (0.30)</td>
<td>0.42 (0.80)</td>
<td>14.40 (0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-3.99x10^{-4} [0.85]</td>
<td>-4.16x10^{-4} [-0.30]</td>
<td>0.00</td>
<td>0.86 (0.64)</td>
<td>0.64 (0.63)</td>
<td>5.43 (0.06)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; $p$-values are mentioned in brackets; critical values for the test of Student amounts to 1.96 at a 5 % confidence level and at 1.64 at a 10 % confidence level.

The theoretical results from table 4 are confirmed in table 5. At daily frequencies, order flows models (model 2) provide a better fit of exchange rate dynamics than traditional models of exchange rate (model 3). Considering the case of the deutschemark/dollar exchange rate, order flows models provide a coefficient of determination ($R^2$) equal to 65 % while the coefficient of determination for traditional models of exchange rate amounts to 5 %.

The better fit of order flows models holds not only at short horizons (as shown here for daily frequencies) but also for long run horizons. Indeed, Berger et al. (2008) analyse interdealer order flows from January 1999 to December 2004 on the euro/dollar and the yen/dollar exchange rates. They show that interdealer order flows have a significant impact on exchange rate variations in the short and medium run but much less explanatory power for long term exchange rate movements. However, although the explanatory power of order flows models falls in the long run, Berger et al. (2008) confirm that the explanatory power of order flows models is still much higher in the long run than the one of traditional exchange rate models.

Such results suggest that order flows provide an answer to the disconnection puzzle of the exchange rate. Indeed order flows contain information about exchange rate fundamentals (Chinn and Moore (2008), Evans and Lyons (2005b, 2008), Rime, Sarno and Sojli (2010)). The only difference between order flows models and traditional models is that the information about exchange rate fundamentals contained in order flows has been processed by market agents. Conversely, traditional models only consider raw (or unprocessed) information about exchange rate fundamentals.

Processed information means that information has been treated by agents. Processed information contains the weight attributed by agents to the various types of information.
included in order flows: fundamental information (public and private) and behavioural
information (public and private). The trading process then includes a third type of
information: the microstructure noise. Therefore order flows is defined as a time-varying
weight of fundamental information (public and private), behavioural information (public and
private) and microstructure information. In comparison, traditional models only consider
public fundamental information. Order flows $X_t$ can thus be defined as:

$$X_t = F_t(\Omega_t, B_t, M_t)$$

The term $\Omega_t$ represents the stock of information about macroeconomic fundamental
considered by an agent at time $t$. This variable includes public information about
fundamentals. The term $B_t$ stands for the behavioural noise affecting agents’ decisions. It
includes the internal and external factors of market psychology. The term $M_t$ is the
microstructure noise. It includes the noise relative to the trading mechanism peculiar to the
foreign exchange market.

Therefore, the higher explanatory and predictive powers of order flows models
compared to traditional models of exchange rate is justified by the fact that order flows
contain processed or treated information while traditional models only consider raw
information. In other words, beyond exchange rate fundamentals, order flows models consider
the behavioural and microstructure components of exchange rates. Conversely, traditional
models ignore such components and take only account of the fundamental information
concerning exchange rates.

Given the importance of the behavioural and the microstructure components at short
horizons relative to long horizons (see Cheung and Wong (2000), Cheung and Chinn (2001),
Cheung, Chinn and Marsh (2004) and appendix C), the explanatory power of order flows
models is far better than the one of traditional exchange rate models in the short run. The
difference in explanatory power between both models decrease in the long run (but is still in
favour of order flows models (Berger et al. (2008))) because both the behavioural and the
microstructure components play a minor role in the determination of the exchange at long run
horizons (see Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and
Marsh (2004) and appendix C).

6. Conclusion

This article aims at understanding the determinants of order flows in the foreign
exchange rate market. We look inside the black box of order flows models to understand why
order flows provide better explanatory and predictive powers of exchange rate dynamics than
traditional models.

We set a theoretical model that takes account of major stylised facts observed in the
foreign exchange market. The model is based on two blocks. The first block is a behavioural
exchange rate model (De Grauwe and Grimaldi (2007)) that provides the characteristics of
customers faced by dealers. The second block is a microstructure model that represents the
trading mechanism peculiar to the foreign exchange market. The microstructure model is a
simultaneous-trade model that has a decentralised and multiple dealer structure.

Simulations from the model replicate important stylized facts observed empirically in
the foreign exchange market.

First, the exchange rate is disconnected from its fundamentals in the short run but not
from order flows. However, in the long run, the exchange rate returns towards its fundamental
value and is close to order flows. Customer and interdealer order flows are highly correlated with exchange rate dynamics at all horizons. Besides the hot potato effect magnifies the amount of interdealer order flows relative to the amount of customer order flows. Secondly, the model shows that the foreign exchange market is intrinsically inefficient. Indeed, information is distorted at two levels in the market. On the one hand, information is distorted by agents’ behaviours. This behavioural noise is split in two factors: internal factors and external factors. Internal factors include notably individual preferences, risk aversion, overreaction to news, specific models used by individuals. External factors cover rumours, mimetism and conventions. On the other hand, information is distorted by the trading mechanism peculiar to the foreign exchange market. This microstructure noise is caused by two factors brought by the hot potato effect: the noise relative to the interpretation of private information by dealers and the noise generated by the passing of undesired positions between dealers.

Thirdly, we argue that order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle. Indeed, order flows models contain information that has been processed by market agents while traditional models only consider raw (or unprocessed) information. Thus, the information in order flows is a time-varying weight of fundamental information (both public and private), behavioural information (both public and private) and microstructure information. In comparison, traditional models only consider public fundamental information. The difference in the types of information considered by the two models explain why order flows models provide higher explanatory and predictive powers of exchange rate dynamics relative to traditional models.
References


Rime Dagfinn, 2000, “Private or Public Information in Foreign Exchange Markets? An Empirical Analysis”, Memorandum, April 2000


Appendix

A. Definition of the different types of order flows

Three types of order flows can be found in the foreign exchange market. All three are related to the three main agents that operate in the foreign exchange market: brokers, market-makers and customers.

Brokers play the role of intermediaries in the foreign exchange market. Given a commission, their task is to match buyers and sellers among market-makers. Brokers are not allowed to take positions in the foreign exchange. Orders between market-makers and brokers are called brokered interdealer order flows. They are registered in electronic systems such as Reuters 3000 Spot Matching or EBS (Electronic Broking Service).

Market-makers negotiate the purchases and sells of currencies with their customers or with other market-makers directly or indirectly through brokers. Orders between market-makers are called direct interdealer order flows. They are registered in Reuters 3000 Dealing System. Usually big banks (such as Deutsche Bank, UBS, Barclays Capital, Citigroup, Royal Bank of Scotland, JP Morgan and HSBC) play the role of market-makers. Contrary to brokers, market-makers are allowed to take positions and thus speculate in the market. These positions are however limited. These limits are often set by risk managers given the degree of experience of traders and the degree of risk in the market. Market-makers are however obliged to close their positions by the end of the day. They often transfer their positions to customers or market-makers situated in other time zones.

Eventually, customers operate in the foreign market to convert currencies with a commercial or with a speculative objective. They are represented by non-financial companies (import-export firms, multinationals), institutional investors (pension funds, hedge funds) and sometimes central banks. Customers transmit their orders to market-makers. Such orders are called customer order flows and are registered in electronic systems of private banks.

One of the most important characteristic of order flows is that order flow is private information. They are not released publicly and are only known by a minority of agents. The most confidential orders are customer order flows followed by direct interdealer order flows and brokered interdealer order flows.

B. Description of the trading mechanism in the foreign exchange market

Order flow is a variable that provides a sign and an amount to a given transaction in the market. Buyers initiated order flows (or buy orders) are positive signed while sellers initiated order flows (or sell orders) are negative signed. Net order flows is the difference between buy orders and sell orders on a given period of time. It is usual to consider net cumulated order flows to analyse the pressure on currency prices. Hence a positive net cumulated order flow is associated to an appreciation of a currency while a negative net cumulated order flow is associated to a depreciation of a currency.

According to Lyons (2001), order flow can be viewed as a mechanism that conveys private information into currency prices. Private information is information that is only known by a minority of agents in the market. A simple example is provided to illustrate the transmission of information in currency prices through order flow.

For sake of simplicity, we assume that every order has an aggressive part (Kyle (1985), Glosten and Milgrom (1985)) and ignore the existence of a limit order book. This assumption is relevant theoretically but not relevant empirically since not all order have an aggressive part empirically and dealers do have a limit order book.
Suppose that the market is initially in equilibrium. Customer 1 analyses the fundamentals of the US dollar and finds that the dollar is over-appreciated against the euro. Customer 1 thus expects a depreciation of the dollar and decides to sell her stock of dollars against euro for 5 millions. Customer 1 hence gives a sell order of -5 to market-maker A. Market-maker A is observing the order flow transmitted by customer 1 and infers the information contained in the order flow. If the market-maker thinks that the customer sells her currency because of a worsening of macroeconomic fundamentals, he will then lower his listed price for the US dollar. Therefore, private information contained in customer 1’s order flow is thus introduced in the price of the currency. At this stage, cumulated order flow and net demand in the market are both equal to -5.

Customer 2 is willing to buy 1 million dollars to market-maker A. The cumulated order flow and the net demand are both equal to -4. Market-maker A sells his whole stock of dollars to market-maker B. Market-maker B infers the negative information contained in the flows provided by market-maker A and decreases her price. Cumulated order flow decreases to -8 while net demand in the market remains unchanged at -4.

This mechanism will repeat itself for market-makers C, D and E. As market-makers take knowledge of the negative information contained in order flows, they decrease the price of the dollar in the market. Finally, the last transaction is materialised by an order of +2 from customer 4. Cumulated order flow amounts to -12 while net demand is equal to zero. The market reaches a new equilibrium where customer 4 buys dollars at a new equilibrium price (i.e. at a lowered price).

Table B summarises the transactions that took place in the market.
Table B: The transmission of information in currency prices through order flows

<table>
<thead>
<tr>
<th>Transaction</th>
<th>Initial Part</th>
<th>Passive Part</th>
<th>Order Flow</th>
<th>Cumulated Order Flow</th>
<th>Customer cumulated net order flow</th>
<th>Net Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Customer 1</td>
<td>MM A</td>
<td>-5</td>
<td>-5</td>
<td>-5</td>
<td>-5</td>
</tr>
<tr>
<td>2</td>
<td>Customer 2</td>
<td>MM A</td>
<td>+1</td>
<td>-4</td>
<td>-4 (= - 5 + 1)</td>
<td>-4 (= - 5 + 1)</td>
</tr>
<tr>
<td>3</td>
<td>MM A</td>
<td>MM B</td>
<td>-4</td>
<td>-8</td>
<td>-4 (= - 4 + 0)</td>
<td>-4</td>
</tr>
<tr>
<td>4</td>
<td>MM B</td>
<td>MM C</td>
<td>-4</td>
<td>-12</td>
<td>-4 (= - 4 + 0)</td>
<td>-4</td>
</tr>
<tr>
<td>5</td>
<td>Client 3</td>
<td>MM C</td>
<td>+2</td>
<td>-10</td>
<td>-2 (= - 4 + 2)</td>
<td>-2</td>
</tr>
<tr>
<td>6</td>
<td>MM C</td>
<td>MM D</td>
<td>-2</td>
<td>-12</td>
<td>-2 (= - 2 + 0)</td>
<td>-2</td>
</tr>
<tr>
<td>7</td>
<td>MM D</td>
<td>MM E</td>
<td>-2</td>
<td>-14</td>
<td>-2 (= - 2 + 0)</td>
<td>-2</td>
</tr>
<tr>
<td>8</td>
<td>Customer 4</td>
<td>MM E</td>
<td>+2</td>
<td>-12</td>
<td>0 (= - 2 + 2)</td>
<td>0 (= - 2 + 2)</td>
</tr>
</tbody>
</table>

Source: Marsh et O’Rourke (2005); MM stands for Market-Maker

Three observations can be highlighted from the above example.

First and along the lines of Lyons (2001), order flows is a mechanism that transmits private information into currency prices. Indeed private information about dollars fundamentals from customer 1 is spread in the market and included in currency prices through order flows between market-makers. Once all the market-makers took knowledge of the negative information, the price of the currency reaches a new equilibrium.

Secondly, table B shows that net demand is strictly equal to cumulated customer order flows. This is due to the assumptions that every order has an aggressive part and also to the exclusion of a limit order book. Had we assume that all trades are not aggressive and also that dealers possess a limit order book, customer order flow would not have been strictly equal to net demand. Customer order flows are the main source of information in the market. Information from customer order flows is then redistributed among market-makers. These redistributions of information take place through the transfer of unwanted positions of currencies by market-makers. They explain the high volume of transactions between dealers in the foreign exchange market (the so-called hot potato effect). However, transactions between market-makers provide no additional information in the market relative to the original private information contained in customer order flows. Transactions between market-makers provide only transitory information through liquidity effects.

Thirdly, transactions between market-makers inflate the amount of flows in the market (as shown in the fifth column of table B related to cumulated order flow). Such flows magnify the effect the initial order flow by customer 1. Hence if the price decreases as it was the case in the previous example, cumulated order flows decrease further more. In the above example, an initial customer order of -5 induces a final cumulated order flow of -12. Given the fact that the price has decreased between the first equilibrium and the second equilibrium, there appears a high correlation between exchange rate and net cumulated order flows. This high correlation justifies the use of order flows as an explanatory variable of exchange rate dynamics.

C. The importance of investor psychology at short run horizons

Beyond macroeconomic fundamentals, one of the major components of exchange rates in the short run is market psychology (Keynes (1936), Hopper (1998)). The importance of this component has been justified by numerous surveys.

Cheung and Wong (2000) survey operators in the foreign exchange market in Tokyo, Hong Kong and Singapore between October 1995 and January 1996. They found that at intraday frequencies exchange rates are exclusively driven by non-fundamental components
(at 99,30 %): speculative forces (30,82 %), over-reaction (24,40 %) and bandwagon effect (24,40 %). In the medium run (shorter than 6 months) factors driving exchange rates are successively technical trading (39,75 %), economic fundamentals (32,14 %), speculative forces (14,0 %) and bandwagon effects (12,13 %). Hence, non-fundamental components still play a major role in explaining exchange rate dynamics (at 67,86 %). In the long run (longer than 6 months), operators consider that economic fundamentals are the main determinants of exchange rates (at 79,56 %).

**Table C.1: Factors determining exchange rate movements (Cheung and Wong (2000))**

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>24,40</td>
<td>12,13</td>
<td>0,84</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30,16</td>
<td>1,98</td>
<td>0,20</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>30,82</td>
<td>14,0</td>
<td>2,30</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,70</td>
<td>32,14</td>
<td>79,56</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>13,92</td>
<td>39,75</td>
<td>17,1</td>
</tr>
</tbody>
</table>

Source: Cheung and Wong (2000); Percentages of respondents in each category are mentioned.

Cheung and Chinn (2001) survey traders operating in the United States foreign exchange market between October 1996 and November 1997. At intraday frequencies, factors that best explain exchange rate dynamics are over-reaction (30,45 %), bandwagon effects (28,20 %) and speculative forces (25,51 %). Hence exchange rates are driven exclusively by non-fundamental components (at 98,56 %). In the medium run (up to 6 months) although economic fundamentals gain some importance (32,10 %), more than 66 % of respondents give credit to non-fundamental forces to explain exchange rate movements. Such non-fundamental forces include technical trading (30,52 %), speculative forces (23,68 %) and bandwagon effects (10,52 %). In the long run (over 6 months), operators consider that exchange rates are determined in majority by economic fundamentals (at 87,40 %).

**Table C.2: Factors determining exchange rate movements (Cheung and Chinn (2001))**

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>28,20</td>
<td>10,52</td>
<td>3,93</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30,45</td>
<td>2,10</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,51</td>
<td>23,68</td>
<td>2,36</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,82</td>
<td>32,10</td>
<td>87,40</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>14,40</td>
<td>30,52</td>
<td>3,14</td>
</tr>
<tr>
<td>Other</td>
<td>0,62</td>
<td>1,08</td>
<td>3,17</td>
</tr>
</tbody>
</table>

Source: Cheung and Chinn (2001); Percentages of respondents in each category are mentioned.

The same results can be found in Cheung, Chinn and Marsh (2004) who survey the United Kingdom foreign exchange market from March 1998 to April 1998. At intraday frequencies, non-fundamental forces determine exchange rates (at 97,7 %); mainly overreaction to news (32,8 %), bandwagon effect (29,3 %) and speculative forces (25,3 %). In the medium run (within 6 months), non-fundamental forces play a major role in the determination of exchange rates (67,2 %) even if economic fundamentals gain importance (31,4 %). In the long run (over 6 months), economic fundamentals are the major determinant of exchange rates (at 82,5 %).
Table C.3: Factors affecting exchange rates (Cheung, Chinn and Marsh (2004))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>29,3</td>
<td>9,5</td>
<td>1</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>32,8</td>
<td>0,7</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,3</td>
<td>30,7</td>
<td>3,1</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,6</td>
<td>31,4</td>
<td>82,5</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>10,3</td>
<td>26,3</td>
<td>11,3</td>
</tr>
<tr>
<td>Other</td>
<td>1,7</td>
<td>1,5</td>
<td>2,1</td>
</tr>
</tbody>
</table>

Source: Cheung, Chinn and Marsh (2004); Percentages of respondents in each category are mentioned.

D. Stationarity tests for series considered in the original model of Evans and Lyons (2001, 2002) (model (1))

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in tables D.1 and D.2.

Table D.1: Stationarity tests for endogenous variables \( \Delta s_t \)

<table>
<thead>
<tr>
<th>Currencies</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-8,84 (0,00)</td>
<td>-8,87 (0,00)</td>
<td>0,08***</td>
</tr>
<tr>
<td>Pound</td>
<td>-8,95 (0,00)</td>
<td>-8,98 (0,00)</td>
<td>0,03***</td>
</tr>
<tr>
<td>Yen</td>
<td>-9,45 (0,00)</td>
<td>-9,45 (0,00)</td>
<td>0,09***</td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; \( p-values \) are mentioned in parenthesis; stars denote a stationary series at a 1 % (***) , 5 % (**), 10 %(*) confidence level.

Table D.2: Stationarity tests for exogenous variables \( \Delta (i_t - i_t^*) \)

<table>
<thead>
<tr>
<th>Currencies</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-8,72 (0,00)</td>
<td>-8,71 (0,00)</td>
<td>0,06***</td>
<td>-9,51 (0,00)</td>
<td>-9,50 (0,00)</td>
<td>0,07***</td>
</tr>
<tr>
<td>Pound</td>
<td>-8,75 (0,00)</td>
<td>-8,75 (0,00)</td>
<td>0,10***</td>
<td>-6,89 (0,00)</td>
<td>-6,92 (0,00)</td>
<td>0,07***</td>
</tr>
<tr>
<td>Yen</td>
<td>-7,91 (0,00)</td>
<td>-7,90 (0,00)</td>
<td>0,04***</td>
<td>-7,57 (0,00)</td>
<td>-7,60 (0,00)</td>
<td>0,18***</td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; \( p-values \) are mentioned in parenthesis; stars denote a stationary series at a 1 % (***) , 5 % (**), 10 %(*) confidence level.

E. Stationarity tests for simulated series from the theoretical model

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in table E.
Table E: Stationarity tests for endogenous variable and exogenous variables simulated by the theoretical model

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_t = F_t )</td>
<td>-1.94</td>
<td>-2.39</td>
<td>1.27</td>
</tr>
<tr>
<td>( \bar{s} = (i_t - i_t^*) )</td>
<td>-3.69</td>
<td>-1.42</td>
<td>0.34</td>
</tr>
<tr>
<td>( V_2 = X_t )</td>
<td>-2.08</td>
<td>-2.65</td>
<td>1.27</td>
</tr>
<tr>
<td>( d{s_t} = dF_t )</td>
<td>-6.10</td>
<td>-18.70</td>
<td>0.04*</td>
</tr>
<tr>
<td>( d\bar{s} = d(i_t - i_t^*) )</td>
<td>-3.68</td>
<td>-2.53</td>
<td>0.18***</td>
</tr>
<tr>
<td>( dV_2 = dX_t )</td>
<td>-9.06</td>
<td>-20.55</td>
<td>0.04*</td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; \( p-values \) are mentioned in parenthesis; stars denote a stationary series at a 1 % (***) , 5 % (**), 10 %(*) confidence level.

F. Definition of the exogenous parameters set for the simulations

Table F presents the parameters values set to run the simulations of the theoretical model of the foreign exchange rate market. The model was calibrated. The main sources for parameter values were De Grauwe and Grimaldi (2007) for the heterogeneous agent model and Lyons (1997) for the microstructure model.

Table F: Parameters values used in the theoretical model

<table>
<thead>
<tr>
<th>Agents</th>
<th>Parameters</th>
<th>Base Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customers</td>
<td>( a_1 )</td>
<td>0.6</td>
</tr>
<tr>
<td>Time ( t )</td>
<td>( a_2 )</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>( \beta_1 )</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>( \beta_2 )</td>
<td>0.4</td>
</tr>
<tr>
<td>( (0&lt;\theta&lt;1) )</td>
<td>( \theta )</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>( \Lambda )</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>( \gamma )</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>( \mu )</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>( T )</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>( n )</td>
<td>50</td>
</tr>
<tr>
<td>Dealers</td>
<td>( \mu_d )</td>
<td>2</td>
</tr>
<tr>
<td>Period 1</td>
<td>( \gamma_1^i )</td>
<td>0.5 if ( O_{F_{customer}}^i ) &lt; ( \overline{O}<em>{F</em>{customer}}^i ), 1.5 if ( O_{F_{customer}}^i ) &gt; ( \overline{O}<em>{F</em>{customer}}^i )</td>
</tr>
<tr>
<td>Time ( t )</td>
<td>( a_1 )</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>( a_2 )</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>( a_4 )</td>
<td>0.1</td>
</tr>
<tr>
<td>Dealers</td>
<td>( \gamma_2^i )</td>
<td>0.5 if ( T_{i,t}^i ) &lt; ( \overline{T}<em>{i,t}^i ), 1.5 if ( T</em>{i,t}^i ) &gt; ( \overline{T}_{i,t}^i )</td>
</tr>
<tr>
<td>Period 2</td>
<td>( b_1 )</td>
<td>0.8</td>
</tr>
<tr>
<td>Time ( t )</td>
<td>( b_2 )</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>( b_3 )</td>
<td>0.2</td>
</tr>
</tbody>
</table>