THE UNIVERSITY OF MELBOURNE

FACULTY OF BUSINESS & ECONOMICS

Melbourne Institute Working Paper Series

Working Paper No. 14/11

Asymmetric Price Impacts of Order Flow on Exchange Rate Dynamics

Viet Hoang Nguyen and Yongcheol Shin

MELBOURNE INSTITUTE®
of Applied Economic and Social Research

Asymmetric Price Impacts of Order Flow on Exchange Rate Dynamics*

Viet Hoang Nguyen† **and Yongcheol Shin**‡

† **Melbourne Institute of Applied Economic and Social Research, The University of Melbourne**

‡ **Leeds University Business School, The University of Leeds**

Melbourne Institute Working Paper No. 14/11

ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 978-0-7340-4246-0

June 2011

* We would like to thank seminar participants at Goethe University, Leeds University Business School (Economics Division and the Centre for Advanced Studies in Finance), and especially Michael Binder, Charlie Cai, Kausik Chaudhuri, Tony Garratt, Matthew Greenwood-Nimmo, Richard Lyons and Kevin Reilly for helpful comments and suggestions. We are also grateful to Martin Evans for providing us with the dataset. Partial financial support from the ESRC (Grant No. RES-000-22-3161) is gratefully acknowledged. The usual disclaimer applies.

Melbourne Institute of Applied Economic and Social Research

The University of Melbourne

Victoria 3010 Australia

***Telephone* (03) 8344 2100**

***Fax* (03) 8344 2111**

***Email* melb-inst@unimelb.edu.au**

***WWW Address* http://www.melbourneinstitute.com**

Abstract

We generalize the portfolio shifts model advanced by Evans and Lyons (2002a; b), and develop the dynamic asymmetric portfolio shifts (DAPS) model by explicitly allowing for possible market under- and overreactions and for asymmetric pricing impacts of order flows. Using the Reuters D2000-1 daily trading data for eight currency markets over a four-month period from 1 May to 31 August 1996, we find strong evidence of a nonlinear cointegrating relationship between exchange rates and (cumulative) order flows: The price impact of negative order flows (selling pressure) is overwhelmingly stronger than that of the positive ones (buying pressure). Through the dynamic multiplier analysis, we find two typical patterns of the price discovery process. The markets following overreactions tend to display a delayed overshooting and a volatile but faster adjustment towards equilibrium whereas the markets following underreactions are generally characterized by a gradual but persistent adjustment. In our model, these heterogeneous adjustment patterns reflect different liquidity provisions associated with different market conditions following under- and overreactions. In addition, the larger is the mispricing, the faster is the overall adjustment speed, a finding consistent with Abreu and Brunnermeier (2002) and Cai et al. (2011). We also find that underreactions are followed mostly by positive feedback trading while overreactions are characterized by delayed overshooting in the short run but corrected by negative feedback trading at longer horizons, the finding is consistent with Barberis et al. (1998) who show that positive short-run autocorrelations (momentum) signal underreaction while negative long-run autocorrelations (reversal) signal overreaction.

JEL classification: C22, F31, G15

Keywords: Exchange rate, order flow, under- and overreaction, asymmetric pricing impacts, asymmetric cointegrating relationship and dynamic multipliers

1 Introduction

With the poor performance of the macro approach to exchange rate determination (Meese and Rogoff, 1983; Frankel and Rose, 1995; Flood and Taylor, 1996), the micro approach has offered a different view to understanding exchange rate movements.[1] The macro approach assumes that all the relevant information is publicly available and directly impounded in the exchange rate. The micro approach, on the other hand, emphasizes that some information is not publicly available but dispersed among agents (Ito, Lyons, and Melvin, 1998). By integrating both public and non–public information gradually into exchange rates, the trading process plays a central role in the micro approach (Lyons, 2001; Evans, 2002; Evans and Lyons, 2005; 2008; Love and Payne, 2008; Rime *et al.*, 2010).[2]

Order flow emerges as the most important micro determinant in conveying relevant information for exchange rate determination. Defined as the difference between signed trades with seller (buyer) initiated trade taking a negative (positive) sign, negative (positive) order flow signals selling (buying) pressure, thus predicting negative (positive) return. However, most existing studies predominantly employ the static return regression, mainly because the continuous market equilibrium is simply assumed (Evans and Lyons, 2002a; b). Alternatively, empirical studies fail to provide conclusive evidence of a cointegrating relationship between the exchange rate and order flow (Rime, 2001; Bjønnes and Rime, 2005; Boyer and van Norden, 2006; and Berger *et al.*, 2008). The continuous market equilibrium holds only if all agents are fully rational, which does not always hold in practice. Furthermore, inconclusive evidence on cointegration may be due to neglecting an important fact that the exchange rate is likely to respond nonlinearly and asymmetrically to news and trades as documented in Luo (2001), Andersen *et al.* (2003), Berger *et al.* (2008) and Wang and Yang (2008). In this regard existing micro studies are limited in uncovering the dynamic, and possibly asymmetric, price discovery process in forex markets.

A growing number of studies document the asymmetric responses to positive and negative information, see Soroka (2006) for a detailed review. Studies in Psychology find that unfavourable information has a stronger impact on impressions than does favourable information (Skowronski and Carlston, 1989; Vonk, 1996). In Politics Bloom and Price (1975) and Lau (1985) provide evidence that negative information has a greater influence on voting behaviour. Moreover, the prospect theory advanced by Kahneman and Tversky (1979) suggests that individuals react asymmetrically to a loss and a gain of the same value with the former inducing a stronger reaction. Hence, if forex traders do respond asymmetrically to positive and negative information, then the imposition of the linear relationship between the exchange rate and order flow is clearly misleading. The path–breaking study by Evans and Lyons (1999, p.20) notes that 'the linearity of our portfolio shifts specification depends crucially on several simplifying assumptions, some of which are rather strong on empirical grounds.'

This paper aims to develop a general model which can address persistent mispricing as well as asymmetric pricing impacts of order flows on exchange rates by significantly extending the portfolio shifts model developed by Evans and Lyons (2002a; b). Our model is also built upon previous studies of 'behaviourally biased' traders and the limited arbitrage in financial markets, e.g. De Long *et al.* (1990a,b), Shleifer and Vishny (1997), Barberis *et al.* (1998), Daniel *et al.* (1998), and Abreu and Brunnermeier (2002, 2003). Specifically, we assume that the potentially biased behaviours of noise traders can cause the market to underreact or overreact in the short run.[3] Rational traders, who are risk–averse, short–lived and faced with fundamental risk, noise trader risk and synchronisation risk or agency problem, often fail to eliminate mispricing imme-

[1] For more complete reviews of the literature, see Sarno and Taylor (2001) and Sager and Taylor (2006).

[2] Evans and Lyons (2008) show that macro news may explain up to 30% of exchange rate variation but two third of its impact is indirect via the trading process.

[3] Daniel *et al.* (1998) attribute under– and overreactions to investor psychology - *overconfidence* and *biased self-attribution*. Barberis *et al.* (1998) posit that under– and overreactions can occur as the result of partially unpredictable movements in investor sentiment - *failures of individual judgement under uncertainty.*

diately and completely.[4] Hence, noise traders could affect the price at least in the short run. Moreover, in our model, persistent underreaction (overreaction) may affect the market liquidity by decreasing (increasing) the speculative demand. As a result, dealers may hold net positions overnight, rendering the market not always at equilibrium. Furthermore, in most micro models, order flows work as the key information integrator channeling the effects of both public and non–public information on exchange rates. To explicitly account for possible asymmetric impacts of favourable and unfavourable information on the exchange rate as documented in Andersen *et al.* (2003), we decompose order flows into buying and selling pressures, representing up (favourable) and down (unfavourable) markets, respectively, and develop the Dynamic Asymmetric Portfolio Shifts (DAPS) model. This framework then allows us to address potential asymmetric pricing impacts of buying and selling pressures through different risk–aversion levels of traders observed in up and down markets.

The distinctive features of our DAPS model lie in its allowance for persistent mispricing, and asymmetric pricing impacts of order flows in both the short– and the long–run, which has been neglected in existing studies. Our model nests the portfolio shifts model of Evans and Lyons (2002b) as a special case in which the market is always at equilibrium and traders respond symmetrically to favourable and unfavourable information. The validity of our theoretical model can be analysed in a flexible manner, employing the Nonlinear Autoregressive Distributed Lag (NARDL) model proposed by Shin, Yu and Greenwood–Nimmo (2009, SYG). Moreover, our model can easily accommodate both the short– and the long–run pricing impact of trades through the dynamic multiplier analysis, providing us a natural framework for assessing market under– and overreaction especially in the short-run. By construction the market underreacts (overreacts) when the short–run price impact of trades is smaller (greater) than its long–run counterpart. In addition, the ability to address the complex dynamic price discovery process through dynamic multipliers renders our model considerably superior to existing approaches.

Using the Reuters D2000–1 daily trading dataset in eight currency spot markets (German mark, British pound, Japanese yen, Swiss franc, French franc, Belgian franc, Italian lira and Netherlandish guilder, all against the US dollar) over a 4–month period from 1 May to 31 August 1996, we find strong evidence in favour of an asymmetric cointegrating relationship between exchange rates and (cumulative) order flows. Specifically, exchange rates respond to trades in a nonlinear fashion with dollar–selling pressure having a stronger pricing impact than dollar–buying pressure. This indicates that traders react more strongly to unfavourable trading information than to the favourable one, supporting our theoretical prediction that agents' risk–aversion degrees are asymmetric in up and down markets. Our empirical results further show that the short–run price impacts of order flow deviate considerably from equilibrium, indicating either market overreaction or underreaction, and suggesting that the equilibrium price is not always reached instantly at the end of each trading day. This finding is generally consistent with the presence of noise traders whose behavioural trades may cause persistent mispricing in the short run, as argued by DeLong *et al.* (1990a; b), Shleifer and Vishny (1997) and Abreu and Brunnermeier (2002, 2003).

Next, we find two typical patterns of the price discovery process among eight markets: one following market overreaction and the other following underreaction. The former is generally characterised by the short–run overshooting and volatile adjustments. Our theoretical model predicts that this is mainly triggered by excess speculative demand. We also find that these possibly destabilising effects related to excess speculative demand are only short–lived, and overreactions are relatively quickly corrected. This suggests that such liquid market condition in

[4]DeLong *et al.* (1990a) suggest that the risk incurred from unpredictable noise traders' beliefs prevents rational arbitrageurs from betting aggressively against them. Shleifer and Vishny (1997) show that professional arbitrageurs are often subject to capital constraints and performance–based arbitrage, and become ineffective even when mispricing is large and significant. Abreu and Brunnermeier (2002) argue that it is the coordination problem among arbitrageurs that causes persistent mispricing.

conjunction with the nature of mispricing (i.e. overreaction) will be likely to offer arbitrageurs a greater incentive to join the adjustment process without delay. On the contrary, a relatively gradual and persistent adjustment pattern is observed in the markets following underreaction. This adjustment pattern can be explained by the low speculative demand associated with the market condition following underreaction. In addition, we find that the larger is the mispricing (as measured by the differential between the short– and the long–run price impacts), the faster is the overall adjustment speed, indicating the greater incentive for arbitrageurs to act on such information, which is consistent with Abreu and Brunnermeier (2002) and Cai *et al.* (2011).

Finally, our empirical results also provide some evidence on feedback trading strategies in forex markets. Underreactions are followed predominantly by positive feedback trading, which may reflect the gradual but dominant arbitraging activity by rational traders. Working as a stabilising force, this pushes the market gradually towards equilibrium. By contrast, we observe delayed overshooting and (often) over–adjusting patterns following overreactions, which may reflect the trend–chasing trading of noise traders (DeLong *et al.*, 1990b; Hong and Stein, 1990). Clearly, this results in market instability over the short–term. At longer horizons, however, overreactions tend to be corrected by negative feedback trading. These findings provide support for two market regularities observed in terms of return autocorrelations: positive short–run autocorrelations (momentum) signal underreaction whilst negative long–run autocorrelations (reversal) signal overreaction, as analysed in Barberis *et al.* (1998) and Daniel *et al.* (1998).

The rest of the paper is organized as follows. In Section 2 we briefly introduce the portfolio shifts model. In Section 3 we develop our extended DAPS model. Section 4 describes the data and presents our main empirical findings. Section 5 provides concluding remarks.

2 Portfolio Shifts Model

We first summarise the portfolio shifts model advanced by Evans and Lyons (2002a; b) (henceforth, EL). EL aims to accommodate the data at daily frequency; to support that a causation runs from order flow to price;[5] and to demonstrate that the price impact of order flow is persistent. Order flow can convey two basic information: one about the stream of future cash flow and the other about the market–clearing discount rate. The EL model is developed on the second information.

At the start of each trading day, uncertain public demands for foreign exchanges are realized through customer–dealer orders which are not publicly observable. Through the trading process, these demand realisations, embedded with information content, affect prices because price concessions are required for the rest of the market to reabsorb them. The EL model follows a Bayesian–Nash Equilibrium (BNE) approach and relies on several key assumptions.

Assumption 2.1 *The economy is a pure exchange one with $T+1$ trading periods, and with two assets - one riskless (gross return normalised to one) and the other risky. The payoff on the risky asset, R_t, is composed of the series of increments, $R_t = \sum_{j=0}^{t} \Delta R_j$ where ΔR_t is the publicly observed increment in period t before trading, and follows the identical and independent normal distribution with zero mean and constant variance, σ_R^2.*

Assumption 2.2 *The operating foreign exchange market is of the dealership–type with N dealers, indexed by $i =, 1..., N$. A continuum of nondealer customers (the public), indexed $w \in [0, 1]$, is large relative to the N dealers.*

Assumption 2.3 *All agents have an identical negative exponential utility function with constant absolute risk aversion (CARA), $U_t = E_t\left[-\exp\left(-\theta W_{t+1}\right)\right]$, where E_t is the expectations operator conditional on the information set at the end of period t, W_{t+1} is the nominal wealth at the end of period $t+1$, and θ is the common constant absolute risk aversion parameter.*

[5]Bacchetta and van Wincoop (2006) provide a theoretical framework under which order flow precedes price.

Assumption 2.4 *The aggregate demand of the public for the risky asset is not perfectly elastic.*

Assumptions 2.2 and 2.3 imply that the risk–bearing capacity of the public is much greater than that of the dealers, ensuring that the dealers have a comparative disadvantage in holding overnight positions. Dealers thus attempt to end each day with no net position in the risky asset.

2.1 Trading Process

Round 1: Dealers trade with the public. At the beginning of each day, all market participants observe the payoff increment, ΔR_t, representing publicly available information. Then, each dealer simultaneously and independently quotes a scalar price, P_{it}^1 (round 1, dealer i, day t), to customers, at which he/she agrees to buy and sell any amount.[6] After trading with customers, each dealer receives a customer order realization, $C_{it}^1 \sim N\left(0, \sigma_C^2\right)$ with $C_{it}^1 < 0$ indicating customer net selling (dealer i's net buying). The aggregate customer–dealer order flow at the end of round 1 can be expressed as

$$C_t^1 = \sum_{i=1}^{N} C_{it}^1. \tag{2.1}$$

C_{it}^1 is observable only to dealer i, representing the portfolio shifts of dealer i's nondealer customers. C_t^1 is unobservable to all agents, representing the aggregate portfolio shifts of the nondealer public.

Round 2: Dealers trade among themselves. Based on the observed C_{it}^1, each dealer simultaneously and independently quotes a price, P_{it}^2, to all other dealers. Dealer i also simultaneously and independently trades on other dealers' quotes. This results in a net interdealer trade in round 2, ΔQ_{it} with $\Delta Q_{it} < 0$ representing dealer i's net–selling. At the close of round 2, all agents observe the interdealer order flow:

$$\Delta Q_t = \sum_{i=1}^{N} \Delta Q_{it}. \tag{2.2}$$

Round 3: Dealers trade again with the public. To share overnight risk, dealers trade again with the public whose trading motive is purely speculative. Conditional on available information, each dealer simultaneously and independently quotes a price, P_{it}^3. Under Assumption 2.4 that the public has finite risk–bearing capacity, dealers set the price, P_{it}^3, such that the public is willing to absorb their inventory imbalances (Evans and Lyons, 2002a; b). Each dealer ends the day with no net position:

$$C_t^1 + C_t^3 = 0, \tag{2.3}$$

where $C_t^3 = \sum_{i=1}^{N} C_{it}^3$ is the unobservable aggregate demand of the public in round 3, and C_{it}^3 is the customer order realization received by and observable only to dealer i. Therefore, P_t^3 reflects information about both ΔR_t and ΔQ_t.

2.2 Static Symmetric Portfolio Shifts Model

The EL model is derived on the basis of several key propositions. Firstly, a quoting strategy of dealers is consistent with symmetric BNE only if all dealers quote a common price at each trading round (Propositions 1 and 2 in Evans and Lyons, 1999; 2002a):

$$P_t^1 = P_t^2 = P_{t-1}^3 + \Delta R_t, \tag{2.4}$$

[6] For simplicity, the price is considered instead of price schedule (bid–offer spread). As noted by Evans and Lyons (2002a; b), the introduction of the price schedule is a straightforward extension.

$$P_t^3 = P_t^2 + \lambda \Delta Q_t, \tag{2.5}$$

where λ is a positive parameter capturing the pricing impact of order flow.

Secondly, the interdealer trade in round 2, Q_{it}, is proportional to the customer order, C_{it}^1, received in round 1 (Proposition 3 in Evans and Lyons, 2002a):

$$\Delta Q_{it} = \alpha C_{it}^1, \ \forall i = 1, ..., N, \tag{2.6}$$

where α is a positive constant. Thus, through the observable ΔQ_t at the end of round 2, all agents can infer the unobservable C_t^1 in round 1.

Thirdly, the aggregate public demand in round 3 can be written as a linear function of the expected returns (Proposition 4 in Evans and Lyons, 2002a):

$$C_t^3 = \gamma \left[E_t \left(P_{t+1}^3 | \Omega_t^3 \right) - P_t^3 \right], \tag{2.7}$$

where Ω_t^3 is the information set available to the public in round 3 of day t, and $\gamma = (\theta \sigma_{R|\Omega}^2)^{-1}$ is the positive price sensitivity of demand coefficient and captures the public's aggregate risk–bearing capacity with θ being the constant absolute risk aversion parameter and $\sigma_{R|\Omega}^2$ being the conditional variance of return.

Combining (2.1)-(2.7), we can derive the link between order flow and price. From (2.1)-(2.3) and (2.6), order flow can be written as

$$C_t^1 = \frac{\Delta Q_t}{\alpha} = -C_t^3. \tag{2.8}$$

Thus, the public's aggregate demand for the risky asset in round 3 can be expressed as

$$P_t^3 = E[P_{t+1}^3 | \Omega_t^3] - \frac{C_t^3}{\gamma} = E[P_{t+1}^3 | \Omega_t^3] + \frac{\Delta Q_t}{\alpha \gamma} = E[P_{t+1}^3 | \Omega_t^3] + \lambda \Delta Q_t, \tag{2.9}$$

where $\lambda = (\alpha\gamma)^{-1} > 0$ captures the pricing impact of order flow and depends on the aggregate risk–bearing capacity of the public, γ, and the dealers' trading behaviour, α. The right–hand side of (2.9) is the cumulative expected payoffs on the risky asset conditional on the available information set, Ω_t^3, which is then adjusted for risk premium in period t, $\lambda \Delta Q_t$ (Evans and Lyons, 1999). (2.9) can be rewritten in terms of payoffs adjusted for risk premia as

$$P_t^3 = \sum_{j=0}^{t} (\Delta R_j + \lambda \Delta Q_j) = R_t + \lambda Q_t, \tag{2.10}$$

where $Q_t = \sum_{j=0}^{t} \Delta Q_j$ is the cumulative order flow. Noting that P_t^3 is the cumulative sum of price changes over t trading periods and assuming that $\Delta P_0^3 = P_0^3$, we can rewrite (2.10) as

$$\sum_{j=0}^{t} \Delta P_j^3 = \sum_{j=0}^{t} (\Delta R_j + \lambda \Delta Q_j). \tag{2.11}$$

Under BNE and assuming that the public holds rational expectations, the price change in round 3 from day $t-1$ to day t is simplified as (Proposition 5 in Evans and Lyons, 2002a):

$$\Delta P_t = \Delta R_t + \lambda \Delta Q_t. \tag{2.12}$$

Evans and Lyons (2002a; b) propose (2.12) as the portfolio shifts model, which explains how the effects of public and non-public information are channeled into price: (i) the direct effect of public information via ΔR_t (directly impounded in price); (ii) the indirect effect of public information via induced order flow, ΔQ_t; and (iii) the direct effect of non-public information via order flow ΔQ_t.

The portfolio shifts model (2.12) crucially depends upon the market clearing condition, (2.3). The pricing impact of trades is also constrained to be constant over time and homogeneous across different market states. In practice, the validity of these constraint is questionable, in particular when not all of the market participants are fully rational and/or when the risk preferences of the public are heterogenous across different market states. Moreover, the static nature of the EL model is unable to provide any prediction for the dynamic adjustment process whenever market disequilibrium occurs.

3 Dynamic Asymmetric Portfolio Shifts Model

We derive a general model which accounts for possible market underreactions and overreactions by allowing for the presence of 'pseudo–informed' noise traders in the public. Importantly, we generalise two restrictive conditions of the EL model, relaxing the equilibrium condition (2.3) and allowing the dynamic price impacts of trades to be asymmetric across different market states.[7]

3.1 Asymmetric Responses to Buying and Selling Pressures

There is growing evidence in Psychology (Skowronski and Carlston, 1989; Vonk, 1996), in Politics (Bloom and Price, 1975; Lau, 1985) and in Economics (Bowman *et al.*, 1999; Andersen *et al.*, 2003; Soroka, 2006), suggesting that individuals respond asymmetrically to positive and negative information with the latter generating stronger reaction. The prospect theory developed by Kahneman and Tversky (1979) offer a descriptive model of decision making in which individuals react more strongly to a loss in value than to a gain of the same magnitude. Figure 1 plots the hypothetical value function proposed by Kahneman and Tversky (1979), and shows that the value function is generally convex for losses and concave for gains, and steeper for losses than for gains. Hence, the drop in value (aggravation) caused by a loss is greater than the increase in value (pleasure) generated by a gain of the same magnitude because individuals are loss–averse. Kahneman *et al.* (1986) also stress that the response of individuals to unfavourable changes is expected to be more intense than that to favourable changes.

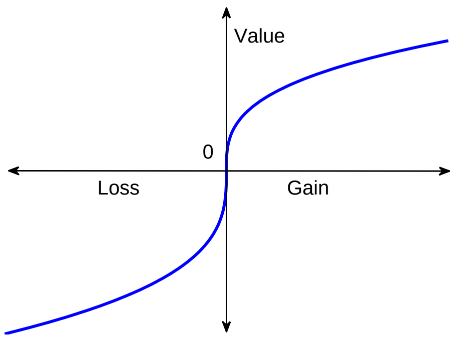


Figure 1: Kahneman and Tversky's Hypothetical Value Function

Under the portfolio shifts framework, selling pressure ($\Delta Q_t < 0$) reaslised in round 2 indicates that the risk–averse public on average sells the risky asset in favor of the riskless one. In other words, it signals bad news or an unfavourable change since it predicts negative return (loss)

[7] Sager and Taylor (2006) sketch several features of a theoretical micro exchange rate model which would correspond closely to the real world. In particular, dealers do not always clear their positions overnight since the public do not absorb dealers' daily imbalances.

for the risky asset in round 3. Conversely, by predicting positive return (gain) buying pressure ($\Delta Q_t > 0$) signals good news or a favourable change. To address the possibility that agents would respond asymmetrically to buying and selling pressures of the same magnitude, we now decompose the interdealer order flow into 'buying' and 'selling' pressures:[8]

$$\Delta Q_t = \Delta Q_t^+ + \Delta Q_t^-, \ t = 0, ..., T, \tag{3.1}$$

where $\Delta Q_t^+ = \max(\Delta Q_t, 0)$ and $\Delta Q_t^- = \min(\Delta Q_t, 0)$. Without loss of generality, we identify ΔQ_t^+ and ΔQ_t^- as signalling the 'up' (favourable) and the 'down' (unfavourable) markets for the risky asset, respectively.

Now consider the exchange between dealers and the public in round 3 under up and down markets. Recall that in this round dealers have to offer price concessions for the public to reabsorb their risky imbalances. In up market dealers want the public to sell the risky asset when it is gaining in value. On the contrary, in down market, dealers want the public to buy the losing–value risky asset. Tversky and Kahneman (1991) note that the rate of exchange between goods can be quite different depending on whether it is acquired or given up. When the public agrees to exchange, they hold the riskless asset in the favourable market while they hold the risky one in the unfavourable market. If the public is loss–averse, the concession required for taking on the risky asset under selling pressure is likely to be greater than that for giving up the risky asset under buying pressure of the same magnitude. The loss–averse feature of the public can be incorporated in the portfolio shifts model by allowing the risk aversion to be greater in down market than in up market as follows:[9]

Assumption 3.1 *All agents have the following negative exponential utility functions:*

$$U_t\left(\frac{c_t}{H_t}\right) = \left\{ \begin{array}{ll} E_t\left[-\exp\left(-\theta^+\left(c_t \backslash H_t\right)\right)\right] & \text{if } \Delta Q_t > 0 \\ E_t\left[-\exp\left(-\theta^-\left(c_t \backslash H_t\right)\right)\right] & \text{otherwise} \end{array} \right\},$$

where c_t is the agent's consumption of the risky asset; H_t is the common habit level of risky–asset consumption for all agents; $\theta^- > \theta^+ > 0$ capture the different absolute risk aversion degrees for all agents in the down and the up markets, respectively.

$\theta^- > \theta^+$ implies that the agent responds more strongly to selling pressure and demand greater price concession to absorb risk than she does to buying pressure of the same magnitude. $c_t > 0$ ($c_t < 0$) indicates that the agent consumes the risky asset (riskless one). H_t is determined by the history of aggregate consumption rather than the history of individual consumption. The habit level is similar to a subsistence level (Samuelson, 1989), a habit index (Chapman, 1998), a habit level (Campbell and Cochrane, 1999), a benchmark level (Abel, 1999), or a subjective reference level (Brandt and Wang, 2003). We then model the habit formation as follows:

$$H_t = \sum_{i=1}^{s} \tau_i |C_{t-i}^3|, \quad 0 < \tau_i < \frac{1}{s}, \ s < t, \tag{3.2}$$

where $C_{t-1}^3, ..., C_{t-s}^3$ are the public's past aggregate consumptions of the risky asset in round 3 (purely speculative demand), and τ_i's are sensitivity parameters. Large aggregate consumptions of the risky asset in the past increase the habit level while small ones decrease it. The habit level specified in (3.2) is external to all agents, and moves slowly in response to consumption with restriction of $0 < \tau_i < s^{-1}$.

Notice that by construction $H_t > 0$ because $H_t = 0$ only if $C_{t-1}^3 = C_{t-2}^3 = ... = C_{t-s}^3 = 0$, meaning that the market does not function for s periods. Hence, the risky–asset consumption

[8]The coverage of zero order flows ($\Delta Q_t = 0$) in our analyzed dataset ranges between 0 and 2% only.

[9]Evans and Lyons (2002c) also measure the utility of agents through their consumption.

ratio, $c_t \backslash H_t > 0$ when $c_t > 0$, and *vice versa*.[10] More importantly, C^3_{t-i}, $i = 1, ...s$, reflects the amount of the risky asset changing hands at the closing price or the risk–bearing capacity of the market at the end of day $t - i$. Hence, H_t is the weighted accumulation of speculative demand and can be considered as a relative measure of market liquidity provision. In particular, an increasing (decreasing) habit level reflects the public's increasing (decreasing) speculative demand, signalling a relatively more liquid (less liquid) market. The market liquidity provision, therefore, can vary over time as the habit level of the public is time-varying. Accordingly, the success of dealers' attempts to clear their inventory imbalances in round 3 of each trading period relies crucially on the time–varying market liquidity provision.[11]

3.2 Market Under- and Overreactions

Recent studies in behavioural finance have provided both theoretical frameworks and pervasive empirical evidence of overreactions and underreactions in stock and foreign exchange markets. In particular, Barberis *et al.* (1998) provide the statistical evidence that investors tend to underreact to good news but overreact to a series of good or bad news. Such events are mainly attributed to investor psychology or sentiment (Barberis *et al.*, 1998; Daniel *et al.*, 1998). To provide a more general portfolio shifts framework with the possibility of market overreactions and underreactions, we introduce the presence of heterogeneous traders and replace Assumption 2.2 of the EL model by

Assumption 3.2 *The operating foreign exchange market is dealership–type with N dealers, indexed by $i =, 1..., N$. A continuum of nondealer customers, indexed $z \in [0, 1]$, consists of both rational and noise traders, and is large relative to the N dealers.*

Our model is built on the previous studies on the behaviours of noise traders, the limits of arbitrage, and market under– and overreactions. In particular, in the presence of noise traders whose investor sentiment is partially unpredictable, mispricing can occur and persist because short–lived and risk–averse rational traders, faced with fundamental risk, noise trader risk (DeLong *et al.*, 1990a), synchronization risk (Abreu and Brunnermeier, 2002) and capital constraints (Shleifer and Vishny, 1997), can only take small positions. Hence, the arbitrage of rational traders is limited and fails to eliminate mispricing completely and immediately. The biased behaviours of noise traders do affect prices at least in the short run. This is a challenge against the efficient market hypothesis (Fama, 1998) which states that rational traders can take advantage of mispricing to earn superior return without bearing any extra risk, removing mispricing immediately.

Lyons (1997) notes that there are two distinctive features of the simultaneous trade model from the rational expectations models. One is that dealers have to contend with inventory shocks, *i.e.* undesired open positions (*hot potato*), which are frequent and nontrivial. The other is that when submitting orders, dealers cannot condition on the market–clearing price level which is unknown and only revealed through the trading process. Suppose that the market underreacts (overreacts) in round 1 of period $t - j$, $j = 1, ..., r \leq s$, as a result of noise traders' biased behaviours. Then, the aggregate customer–dealer trade in round 1, C^1_{t-j}, does not reflect the correct market condition in period $t - j$, denoted by C^{1*}_{t-j}, i.e. $C^1_{t-j} < C^{1*}_{t-j}$ ($C^1_{t-j} > C^{1*}_{t-j}$). This deviation is then passed on to dealers in trading rounds 2 and 3 of period $t-j$, causing mispricing, i.e. $P^3_{t-j} < P^{3*}_{t-j}$ ($P^3_{t-j} > P^{3*}_{t-j}$) with P^{3*}_{t-j} denoting the equilibrium price level. Because of the limited arbitrage, market under– or overreaction and mispricing may persist beyond trading period $t - j$.

[10] For a representative agent, $c_t \backslash H_t > 0$ ($c_t \backslash H_t < 0$) signals ΔQ^+ (ΔQ^-).

[11] Abel (1999) also measure the utility of agents by the consumption ratio in which case the absolute risk aversion of all agents with respect to consumption, defined as $\theta_t = -\left(\frac{U''(c_t)}{U'(c_t)}\right) = \left(\frac{\theta}{H_t}\right)$, is time–varying due to the time–varying habit level H_t. The market liquidity condition, therefore, varies over time.

By construction, the persistent market underreaction (overreaction) periods $t-1, ..., t-r$ could decrease (increase) the habit level in period t, resulting in a relatively less (more) liquid market. Consequently, dealers may not be able to unload their risky imbalances in a liquidity–constrained market, ending up holding net positions overnight. Alternatively, in a relatively liquid market, dealers may not only clear their initial imbalances but also take on new (undesired) imbalances in opposite direction due to excess speculative demand.[12] To accommodate this possibility, we relax the market clearing condition, (2.3) of the EL model as follows:

$$C_t^1 + C_t^3 = \delta_t, \tag{3.3}$$

where δ_t is the unobservable market aggregate imbalance given by

$$\delta_t = \sum_{i=1}^{N} \delta_{it}, \;\; \delta_{it} \sim (0, \sigma_\delta^2), \;\; \sigma_\delta^2 \neq 0, \tag{3.4}$$

and δ_{it} is the order imbalance held by dealer i. For convenience, we define $I_t = -\delta_t$ such that I_t is the aggregate inventory imbalance of all dealers at the end of period t. Under (3.3) and (3.4), the market is not always at equilibrium at the end of each trading period though the market will return to equilibrium in the long run.

Depending on the dealers' aggregate inventory imbalance position (I_t), we project three likely outcomes at the end of each period in Table 1. *Case* 1 shows that the market is at equilibrium because the dealers can clear their inventory imbalances. *Cases* 2 and 3 describe the situations where underreaction and overreaction result in market disequilibrium in period t. In *Case* 2, though the dealers follow the quoting strategy in (2.5), their quoted price in trading round 3, P_t^3, does not induce the public to reabsorb the risky imbalances due to insufficient speculative demand (decreasing habit level H_t). This means that P_t^3 does not include the sufficient price concession (risk premium) accounting for the low liquidity condition. As such, the absolute price level, P_t^3, is smaller than its equilibrium counterpart, P_t^{3*}, *i.e.* market underreaction. Turning to *Case* 3, due to excess speculative demand (increasing habit level H_t), the dealers not only clear their initial inventory imbalances from rounds 1 and 2, but also takes on new inventory imbalances in opposite sign with their quoted price in round 3, P_t^3. This means that P_t^3 offers a higher price concession than required under the high liquidity condition. Therefore, the absolute price level, P_t^3, is greater than its equilibrium counterpart, P_t^{3*}, *i.e.* market overreaction.

Case	R. 1 C_t^1	R. 2 ΔQ_t	R. 3 C_t^3	C_t^1 vs. C_t^3	I_t $(=-\delta_t)$	Speculative Demand	Market Condition
1	$(+)$ $(-)$	$(+)$ $(-)$	$(-)$ $(+)$	$\lvert C_t^{1+}\rvert = \lvert C_t^{3-}\rvert$ $\lvert C_t^{1-}\rvert = \lvert C_t^{3+}\rvert$	0 0	Sufficient	Equilibrium
2	$(+)$ $(-)$	$(+)$ $(-)$	$(-)$ $(+)$	$\lvert C_t^{1+}\rvert > \lvert C_t^{3-}\rvert$ $\lvert C_t^{1-}\rvert > \lvert C_t^{3+}\rvert$	$(-)$ $(+)$	Insufficient	Underreaction
3	$(+)$ $(-)$	$(+)$ $(-)$	$(-)$ $(+)$	$\lvert C_t^{1+}\rvert < \lvert C_t^{3-}\rvert$ $\lvert C_t^{1-}\rvert < \lvert C_t^{3+}\rvert$	$(+)$ $(-)$	Excess	Overreaction

*'R.' denotes Trading Round. (+) and (−) denotes buying and selling pressure, respectively.

Table 1: Possible Outcomes of Each Trading Period

Notice that, under *Case* 2 the dealers' aggregate inventory imbalance (I_t) and market order flows in rounds 1 and 2 of period t (which indicate the market direction) are of the opposite signs, suggesting that the dealers' risk exposure and the market direction are negatively correlated. By

[12] Chordia *et al.* (2002) show that aggregate order imbalances in the stock market reduce market liquidity and make market–maker's inventories experience periodic strains. Such inventory strains could persist beyond a trading day, leaving extended effects on liquidity.

contrast, the dealers' risk exposure is positively correlated with the market direction under *Case* 3. In sum, *Cases* 2 and 3 show that the dealers may hold undesired imbalances overnight due to mispricing and insufficient or excess speculative demand. We summarise the important implication of this discussion in the following assumption:

Assumption 3.3 *Let ω be the correlation coefficient between the interdealer order flow (ΔQ_t) and the dealers' aggregate inventory imbalance (I_t). Then, $\omega < 0$ ($\omega > 0$) indicates market underreaction (overreaction), reflecting that the market speculative demand is insufficient (excess).*

The mainstream literature on market efficiency and noise trading (Figlewski, 1979; Kyle, 1985; Campbell and Kyle, 1988; DeLong *et al.*, 1990b), suggest that the adjustment process towards market equilibrium consists of two competing forces: one by the informed rational traders and the other by the pseudo–informed noise traders. The former rationally counters deviations of prices from equilibrium, hence working as the stabilising force. The latter destabilises the market by buying when prices are high and selling when prices are low on average, thus driving prices away from fundamentals. DeLong *et al.* (1990b) suggest that noise traders may also follow the trading strategy of rational traders through positive feedback trading, resulting in market instability. In general, trades of rational traders move prices in the direction of, even if not all the way to, fundamentals. This dampens noise–driven price movements but does not eliminate them (DeLong *et al.*, 1990b). Hence, we expect that the heterogeneous trading behaviours of rational and noise traders will determine the (possibly asymmetric) dynamic price adjustment process towards equilibrium following market overreaction or underreaction.

3.3 Dynamic Asymmetric Portfolio Shifts Model

The market disequilibrium condition (3.3) can be generalised in the up and the down markets respectively as follows:

$$C_t^{1+} = \frac{\Delta Q_t^+}{\alpha} = -C_t^{3-} + \delta_t^U, \tag{3.5}$$

$$C_t^{1-} = \frac{\Delta Q_t^-}{\alpha} = -C_t^{3+} + \delta_t^D, \tag{3.6}$$

where δ_t^U and δ_t^D are the (accumulated) market imbalances in the up and the down markets such that $\delta_t = \delta_t^U + \delta_t^D$.[13] As before, we redefine $I_t^U(= -\delta_t^U)$ and $I_t^D(= -\delta_t^D)$ as the dealers' inventory imbalances in the up and the down market. C_t^{1+} (C_t^{1-}) represents the aggregate customer–dealer order in the up (down) market at the end of round 1 while C_t^{3-} (C_t^{3+}) is the public's aggregate demand for the risky asset at the end of round 3 in the up (down) market.

We modify (2.9) and express the price level at the end of round 3 in up market as

$$P_t^{3+} = E\left(P_{t+1}^3 | \Omega_t^3\right) + \frac{\Delta Q_t^+}{\alpha\gamma^+} - \frac{\delta_t^U}{\gamma^+} = R_t^+ + \lambda^+ Q_t^+ - \frac{\delta_t^U}{\gamma^+}, \tag{3.7}$$

where $P_t^{3+} = \sum_{j=0}^t \Delta P_j^{3+}$, $R_t^+ = \sum_{j=0}^t \Delta R_j^+$, and $Q_t^+ = \sum_{j=0}^t \Delta Q_j^+$. Here ΔP_j^{3+} and ΔR_j^+ are the price change and payoff increment associated with the up market (ΔQ_j^+). $\gamma^+ = (\theta^+ \sigma_{R|\Omega}^2)^{-1}$ and $\lambda^+ = (\alpha\gamma^+)^{-1}$ capture the risk bearing capacity of the pubic and the price impact of trades in the up market, respectively. Similarly, the price level at the end of round 3 in the down market can be written as

$$P_t^{3-} = R_t^- + \lambda^- Q_t^- - \frac{\delta_t^D}{\gamma^-}, \tag{3.8}$$

[13] δ_t^U and δ_t^D can be either positive or negative, implying that both *Cases* 2 and 3 can be observed in the up and the down markets.

where $P_t^{3-} = \sum_{j=0}^{t} \Delta P_j^{3-}$, $R_t^- = \sum_{j=0}^{t} \Delta R_j^-$, $Q_t^- = \sum_{j=0}^{t} \Delta Q_j^-$, $\gamma^- = (\theta^- \sigma^2_{R|\Omega})^{-1}$ and $\lambda^- = (\alpha\gamma^-)^{-1}$. Combining (3.7) and (3.8), we obtain the asymmetric level relationship between the price and (cumulative) order flows as follows:

$$P_t = R_t + \lambda^+ Q_t^+ + \lambda^- Q_t^- + \xi_t, \tag{3.9}$$

where $P_t = P_t^{3+} + P_t^{3-}$, $R_t = R_t^+ + R_t^-$ by construction and $\xi_t = -\left(\frac{\delta_t^U}{\gamma^+} + \frac{\delta_t^D}{\gamma^-}\right)$ captures the dealers' aggregate inventory imbalance. ξ_t crucially relies upon the (asymmetric) risk–bearing capacities of the public in up and down markets, γ^+ and γ^-, respectively. Notice that if the public is more risk–averse in down market than in up market, their risk–bearing capacity will be smaller in down market. Accordingly, the public demands a greater price concession to absorb selling pressure than they do to absorb buying pressure of the same magnitude, indicating a stronger price impact of selling pressure.

As discussed in the previous subsection, the inventory imbalance of the dealers can persist beyond a trading day. Hence, we make the following assumption:

Assumption 3.4 *ξ_t follows an $AR(1)$ process:*

$$\xi_t = \rho\xi_{t-1} + u_t,$$

where the parameter ρ captures the degree of persistence in the dealers' inventory imbalance, and u_t is the iid innovation with zero mean and constant variance σ_u^2.

For convenience, we rewrite Assumption 3.4 as

$$\Delta\xi_t = \psi\xi_{t-1} + u_t, \tag{3.10}$$

where $\psi = (\rho - 1)$ is the parameter measuring the speed of adjustment. Taking the first difference of (3.9) and using (3.10), we obtain the following error correction representation of the model:

$$\Delta P_t = \psi\xi_{t-1} + \Delta R_t + \lambda^+ \Delta Q_t^+ + \lambda^- \Delta Q_t^- + u_t, \tag{3.11}$$

where $\xi_t = P_t^3 - R_t - \lambda^+ Q_t^+ - \lambda^- Q_t^-$ is the error correction term associated with the asymmetric level relationship (3.9).

There is a growing literature documenting evidence of feedback trading behaviour in both foreign exchange and other securities markets (Hasbrouck, 1991; Daníelsson and Love, 2006; and Evans and Lyons, 2008). Furthermore, Cohen and Shin (2003) suggest that traders tend to adjust their positions in a series of trades rather than all at once. Hence, we may expect to observe (possibly) counteractive feedback trading strategies by rational and noise traders over several periods. In order to explicitly allow for the presence of feedback trading behaviors within our model, we assume:[14]

Assumption 3.5 *The feedback trading behaviours of agents can be captured by the following reduced form regression for the interdealer order flow, ΔQ_t:*

$$\Delta Q_t = \sum_{i=1}^{p} \phi_{Pi}\Delta P_{t-i} + \sum_{j=1}^{q} \phi_{Qj}^+ \Delta Q_{t-j}^+ + \sum_{j=1}^{q} \phi_{Qj}^- \Delta Q_{t-j}^- + v_t, \tag{3.12}$$

where ϕ_{Pi}, ϕ_{Qi}^+ and ϕ_{Qi}^- are feedback trading coefficients and v_t is the iid innovation with zero mean and constant variance σ_v^2. ϕ_{Pi}, ϕ_{Qi}^+ and $\phi_{Qi}^- > 0$ (ϕ_{Pi}, ϕ_{Qi}^+ and $\phi_{Qi}^- < 0$) signal positive (negative) feedback trading strategy.

[14] Our feedback trading specification is similar to those in Hasbrouck (1991) and Cohen and Shin (2003). Contemporaneous feedback trading, considered by Daníelsson and Love (2006), is ruled out because P_t^3 is set in trading round 3 of period t by dealers based on their aggregated information from trading round 2, ΔQ_t. Thus, if dealers follow the quoting strategy in (2.5), then $\Delta P_t = P_t^3 - P_{t-1}^3$ is clearly determined by ΔQ_t.

Notice that the interdealer order flow innovation, v_t in (3.12), now dictates the market direction (ΔQ_t) after controlling for the feedback trading behaviours. Hence, we combine Assumptions 3.3 and 3.5, and express the relationship between u_t and v_t formally as

$$u_t = \omega v_t + e_t, \ e_t \sim iid(0, \sigma_e^2), \tag{3.13}$$

where ω is the market reaction parameter capturing the contemporaneous association between the dealers' inventory imbalance and the market direction (the interdealer order flow). v_t is uncorrelated with e_t by construction. Combining (3.12) and (3.13), we obtain

$$u_t = \omega \left(\Delta Q_t - \sum_{i=1}^{p} \phi_{Pi} \Delta P_{t-i} - \sum_{j=1}^{q} \phi_{Qj}^{+} \Delta Q_{t-j}^{+} - \sum_{j=1}^{q} \phi_{Qj}^{+} \Delta Q_{t-j}^{-} \right) + e_t. \tag{3.14}$$

Then, substituting (3.14) in (3.11), we obtain the following error correction model called the dynamic asymmetric portfolio shifts (DAPS) model:

$$\Delta P_t = \psi \xi_{t-1} + \Delta R_t + \kappa^+ \Delta Q_t^+ + \kappa^- \Delta Q_t^- + \sum_{i=1}^{p} \pi_i \Delta P_{t-i} + \sum_{j=1}^{q} \varphi_j^+ \Delta Q_{t-j}^+ + \sum_{j=1}^{q} \varphi_j^- \Delta Q_{t-j}^- + e_t \tag{3.15}$$

where $\kappa^+ = \lambda^+ + \omega$, $\kappa^- = \lambda^- + \omega$, $\pi_i = -\omega \phi_{Pi}$, $\varphi_j^+ = -\omega \phi_{Qj}^+$ and $\varphi_j^- = -\omega \phi_{Qj}^-$. It is clear from (3.15) that κ^+ and κ^- represent the short–run contemporaneous price impacts incorporating the correlation between the dealers' inventory imbalance and the market direction. This shows that κ^+ and κ^- can be different from the long–run equilibrium price impacts, λ^+ and λ^-.

This model explicitly takes into account: (i) the persistent mispricing and the dealers' persistent inventory imbalance , (ii) the correlation between the dealers' inventory imbalance and the market direction, (iii) different feedback trading strategies, and (iv) the asymmetric pricing impacts of signed order flows in the short– and the long–run. In general, under the DAPS framework, the behavioural trades of noise traders may cause short–run market disequilibrium while the different risk aversion degrees of the agents result in the asymmetric pricing impacts of order flows in the up and the down markets. Clearly, when the market underreacts ($\omega < 0$), the contemporaneous price impacts are smaller than their equilibrium counterparts, *i.e.* $\kappa^+ < \lambda^+$ and $\kappa^- < \lambda^-$, and *vice versa*. The validity of the DAPS model and its associated assumptions can be examined through testing several hypotheses in the empirical section.

As discussed in Section 3.2, the feedback trading strategies of rational and noise traders following market under– and overreactions will determine the pattern and the direction of the dynamic price discovery process. In theory, the market underreaction ($\omega < 0$) is expected to be followed by positive feedback trading (*i.e.* ϕ_{Pj}, ϕ_{Qj}^+ and $\phi_{Qj}^- > 0$ in (3.12)) while negative feedback trading (*i.e.* ϕ_{Pj}, ϕ_{Qj}^+ and $\phi_{Qj}^- < 0$) is expected to follow the market overreaction ($\omega > 0$). Barberis *et al.* (1998) and Daniel *et al.* (1998) make similar predictions and both adjustment patterns stabilize the market by pushing the price towards its equilibrium. This is likely to reflect the behaviour of rational traders (arbitrageurs). However, with the presence of behavioural traders in practice, any dynamic adjustment pattern could happen. For example, negative feedback trading could follow market underreaction whilst positive feedback trading immediately after market overreaction may cause the price to overshoot (DeLong *et al.*, 1990b). These adjustment patterns clearly destabilize the market and move the price further away from its equilibrium. Generally, in the context of the DAPS model, (3.15), we can predict that π_i, φ_j^+ and $\varphi_j^- > 0$ signal the equilibrium–driven feedback trading strategies of the stabilising force while π_i, φ_j^+ and $\varphi_j^- < 0$ represents the feedback trading strategies of the destabilising force, irrespective of whether the market is underreacting or overreacting. Hence, we may conclude that which of the two competing forces, the noise and the rational traders, prevails in the dynamic price discovery process will be an important issue determined mainly empirically.

3.4 Dynamic Price Adjustment Process

We examine in details how the market evolves dynamically towards equilibrium under the DAPS framework. For simplicity, we suppose that the market is at disequilibrium in period t and returns to equilibrium after k $(\leq T-t)$ periods. The only new information is given by the deviation from the fundamental value and the (unobservable) aggregate inventory imbalance of the dealers in period t. These will then be impounded in the price through the trading process.

Though each dealer has information about his/her own inventory imbalance, δ_{it}, all the dealers still quote common prices in three trading rounds to avoid arbitrage opportunities (Evans and Lyons, 1999). Therefore, the dealers' quoting strategies can be written as

$$P^1_{t+j} = P^2_{t+j} = P^3_{t+j-1} + \Delta R_{t+j}, \tag{3.16}$$

$$P^3_{t+j} = P^2_{t+j} + \lambda \Delta Q_{t+j}. \tag{3.17}$$

Combining (3.16) and (3.17), we obtain:

$$P^3_{t+j} = P^3_{t+j-1} + \Delta R_{t+j} + \lambda \Delta Q_{t+j}. \tag{3.18}$$

We provide detailed analyses of the adjustment processes in the presence of market underreaction (*Case* 2) and overreaction (*Case* 3) only in the up market. The adjustment processes in the down market can be similarly analysed with the opposite dynamic price movements.

3.4.1 Dynamic Price Discovery with respect to the Market Underreaction

When the market underreacts initially, the market disequilibrium in period t can be expressed as (see (3.5))

$$C^{1+}_t + C^{3-}_t = \delta^{U+}_t, \tag{3.19}$$

where $\delta^{U+}_t > 0$ is due to the insufficient speculative demand of the public in round 3. Then, the disequilibrium price level can be written as

$$P^{3+}_t = R^+_t + \lambda^+ Q^+_t - \frac{\delta^{U+}_t}{\gamma^+}. \tag{3.20}$$

Defining the equilibrium price by

$$P^{*+}_t = R^+_t + \lambda^+ Q^{*+}_t, \tag{3.21}$$

where the superscript '*' indicates the equilibrium level, we can express the mispricing as

$$P^{*+}_t - P^{3+}_t = \lambda^+ (Q^{*+}_t - Q^+_t) + \frac{\delta^{U+}_t}{\gamma^+} > 0. \tag{3.22}$$

(3.22) shows that the mispricing consists of the two terms: $\lambda^+(Q^{*+}_t - Q^+_t) > 0$ represents the deviation from fundamentals and $\delta^{U+}_t/\gamma^+ > 0$ reflects the unobserved (additional) price concession required to compensate for the insufficient speculative demand.

We now discuss the possible trading outcomes in period $t+1$ in the presence of both rational and noise traders. Denote the aggregate trade orders of rational and noise traders in round 1 by F_t and N_t $(\neq 0)$, respectively. Notice that F_t is equilibrium–driven while N_t moves in the same or the opposite direction to F_t. Thus, the absolute values of F_t and N_t represent the relative strengths of rational and noise traders in period t. Let a_t be the time–varying probability that $|F_t| < |N_t|$, and b_t the time–varying probability that F_t and N_t are of the same direction (i.e. both rational and noise traders buy or sell). (3.22) suggests that rational speculators will buy the risky asset to push its price towards its equilibrium level while noise speculators could buy or sell the risky asset. Depending on the relative strength of the two types of traders (a_t) and

Relative Strength	Outcome	Probability
1. $\lvert F_{t+1}\rvert < \lvert N_{t+1}\rvert$	1a. $F_{t+1}^{+}+N_{t+1}^{+}=C_{t+1}^{++}$	$a_{t+1}b_{t+1}$
	1b. $F_{t+1}^{+}+N_{t+1}^{-}=C_{t+1}^{-}$	$a_{t+1}\left(1-b_{t+1}\right)$
2. $\lvert F_{t+1}\rvert \geq \lvert N_{t+1}\rvert$	2a. $F_{t+1}^{+}+N_{t+1}^{+}=C_{t+1}^{++}$	$\left(1-a_{t+1}\right)b_{t+1}$
	2b. $F_{t+1}^{+}+N_{t+1}^{-}=C_{t+1}^{+}$	$\left(1-a_{t+1}\right)\left(1-b_{t+1}\right)$

*C_{t+1} denotes the aggregate customer–dealer trade in round 1 of period $t+1$. Specifically, C_{t+1}^{++} denotes that F_{t+1} and N_{t+1} are of the same direction, C_{t+1}^{+} (C_{t+1}^{-}) denotes that they are of opposite directions with the dominance of rational (noise) traders. $Pr(\lvert F_{t+1}\rvert < \lvert N_{t+1}\rvert) = a_{t+1}$ and $Pr[N_{t+1}^{+}] = b_{t+1}$).

Table 2: Trading Outcomes Following Market Underreaction

the trading strategies of noise traders (b_t), we summarize four possible outcomes in round 1 of period $t+1$ in Table 2.[15]

The four outcomes in Table 2 can be grouped into three events as follows:

- Event A: gradual equilibrium adjustment (Case 2b) with $\Pr(A) = (1-a_{t+1})(1-b_{t+1})$,
- Event B: fast but possible over–adjustment (Cases 1a and 2a) with $\Pr(B) = a_{t+1}b_{t+1} + (1-a_{t+1})\,b_{t+1} = b_{t+1}$,
- Event C: counter–equilibrium adjustment (Case 1b) with $\Pr(C) = a_{t+1}(1-b_{t+1})$.

This analysis suggests the following scenarios. First, Event B is independent of the probability that which traders dominate the market (a_t). Hence, the higher the probability that noise traders follow the trading strategy of rational traders (say, $b_t > 1/2$) is, the more likely Event B is to occur. Second, if noise traders mostly adopt the opposite trading strategy of rational traders (i.e. b_t is quite low), then the market will experience either Event A or Event C. Which of these two events is more likely to occur crucially depends on who dominates the market (i.e. a_t). Moreover, the overall adjustment patterns associated with Events A and B are characterized by positive feedback trading which mainly stabilises the market. By contrast, Event C implies the dominance of negative feedback trading by noise traders which destabilises the market by moving the price further away from its equilibrium.

The adjustments in period $t+j$ for $j = 2, ..., k$, can be analyzed similarly. When the market returns to equilibrium in period $t+k$, the following conditions should be satisfied:

$$P_{t+k}^{3} = P_t^{*+} \text{ and } \sum_{j=0}^{k}\left(C_{t+j}^{1} + C_{t+j}^{3}\right) = 0. \tag{3.23}$$

Imposing the first condition in (3.23), we obtain:

$$P_{t+k}^{3} - P_t^{3+} = \lambda^{+}(Q_t^{*+} - Q_t^{+}) + \frac{\delta_t^{U+}}{\gamma^{+}} \tag{3.24}$$

Using the identity, $P_{t+k}^{3} = \sum_{j=1}^{k}\left(\Delta R_{t+j} + \lambda^{+}\Delta Q_{t+j}\right)$, we can rewrite (3.24) as

$$\sum_{j=1}^{k}\left(\Delta R_{t+j} + \lambda^{+}\Delta Q_{t+j}\right) = \lambda^{+}(Q_t^{+*} - Q_t^{+}) + \frac{\delta_t^{U+}}{\gamma^{+}}. \tag{3.25}$$

(3.25) shows that the cumulative adjusted risk premia over k periods (the left–hand side component) is equal to the price deviation from its fundamental value and the unobserved price

[15]Trivially, no adjustment is made if $F_{t+1} = -N_{t+1}$ as in Case 2b.

concession in period t (to compensate for the insufficient speculative demand). The market returns to equilibrium only if the deviation is corrected and the unobserved price concession is fully impounded in the price after k trading periods. Furthermore, using (3.19), the second condition in (3.23) can be expressed as

$$\sum_{j=1}^{k}\left(C_{t+j}^{1}+C_{t+j}^{3}\right)=-\delta_t^{U+}, \tag{3.26}$$

which shows that the dealers can successfully clear their period–t imbalances over k periods.

3.4.2 Dynamic Price Discovery with respect to the Market Overreaction

The market disequilibrium following market overreaction can be expressed as (see (3.5)):

$$C_t^{1+}+C_t^{3-}=\delta_t^{U-}, \tag{3.27}$$

where $\delta_t^{U-}<0$ is due to excess speculative demand. Then, the disequilibrium price level can be expressed as

$$P_t^{3+}=R_t^{+}+\lambda^{+}Q_t^{+}-\frac{\delta_t^{U-}}{\gamma^{+}}. \tag{3.28}$$

Using the equilibrium price level in (3.21), we can express the mispricing as

$$P_t^{*+}-P_t^{3+}=\lambda^{+}(Q_t^{*+}-Q_t^{+})+\frac{\delta_t^{U-}}{\gamma^{+}}<0, \tag{3.29}$$

showing that the quoted price in round 3, $\left(P_t^{3+}\right)$, deviates from fundamentals by $\lambda^{+}(Q_t^{+*}-Q_t^{+})<0$, and includes an additional concession of $\delta_t^{U-}/\gamma^{+}<0$ than required when the speculative demand is excessive.

It is clear from (3.29) that rational speculators will sell the risky asset to reduce the price to its equilibrium level while noise speculators either buy or sell the risky asset. Again, depending on the relative strength of the two types of traders (a_t) and the trading strategies of noise traders (b_t), we summarize four outcomes in round 1 of period $t+1$ in Table 3.

Relative Strength	Outcome	Probability
1. $\lvert F_{t+1}\rvert<\lvert N_{t+1}\rvert$	1a. $F_{t+1}^{-}+N_{t+1}^{-}=C_{t+1}^{--}$	$a_{t+1}b_{t+1}$
	1b. $F_{t+1}^{-}+N_{t+1}^{+}=C_{t+1}^{+}$	$a_{t+1}\left(1-b_{t+1}\right)$
2. $\lvert F_{t+1}\rvert\geq\lvert N_{t+1}\rvert$	2a. $F_{t+1}^{-}+N_{t+1}^{-}=C_{t+1}^{--}$	$\left(1-a_{t+1}\right)b_{t+1}$
	2b. $F_{t+1}^{-}+N_{t+1}^{+}=C_{t+1}^{-}$	$\left(1-a_{t+1}\right)\left(1-b_{t+1}\right)$

*C_{t+1} denotes the aggregate customer-dealer trade in round 1 of period $t+1$. Specifically, C_{t+1}^{--} denotes that F_{t+1} and N_{t+1} are of the same direction, C_{t+1}^{-} (C_{t+1}^{+}) denotes that they are of opposite directions with the dominance of rational (noise) speculators. $Pr(\lvert F_{t+1}\rvert<\lvert N_{t+1}\rvert)=a_{t+1}$ and $Pr[N_{t+1}^{-}]=b_{t+1}$).

Table 3: Trading Outcomes Following Market Overreaction

The four outcomes in Table 3 can be grouped into three events as follows:

- Event D: gradual equilibrium adjustment (Case 2b) with $\Pr(D)=\left(1-a_{t+1}\right)\left(1-b_{t+1}\right)$,
- Event E: fast but possible over–adjustment (Cases 1a and 2a) with $\Pr(E)=a_{t+1}b_{t+1}+\left(1-a_{t+1}\right)b_{t+1}=b_{t+1}$,
- Event F: overshooting adjustment (Case 1b) with $\Pr(F)=a_{t+1}\left(1-b_{t+1}\right)$.

We have the following scenarios. When most noise traders follow the equilibrium–driven trading strategy of rational traders (*i.e.* b_t is relatively high), the market is likely to experience Event E. On the other hand, when more noise traders adopt the counter–equilibrium trading strategy (*i.e.* b_t is relatively low), Event D (Event F) is more likely to occur if rational (noise) traders prevail. Overall adjustment patterns associated with Events D and E display the negative feedback trading strategy, mainly stabilising the market. By contrast, Event F implies the dominance of the positive feedback trading by noise traders, which destabilises the market.

The adjustments in period $t+j$ for $j=2,...,k$, can be analyzed similarly. When the market returns to equilibrium in period $t+k$, both conditions in (3.23) should also be satisfied. Using similar derivations of (3.25) and (3.26), we obtain:

$$\sum_{j=1}^{k}\left(\Delta R_{t+j}+\lambda^{+}\Delta Q_{t+j}\right)=\lambda^{+}(Q_t^{+*}-Q_t^{+})+\frac{\delta_t^{U-}}{\gamma^{+}}, \tag{3.30}$$

$$\sum_{j=1}^{k}\left(C_{t+j}^{1}+C_{t+j}^{3}\right)=-\delta_t^{U-}. \tag{3.31}$$

(3.30) indicates that the market returns to equilibrium only if both the deviation of the price from fundamentals and the surplus price concession in period t (due to the excess speculative demand) are fully discounted from the price after k trading periods. (3.31) suggests that the public fully reabsorbs the risky imbalances of the dealers in period t over k periods.

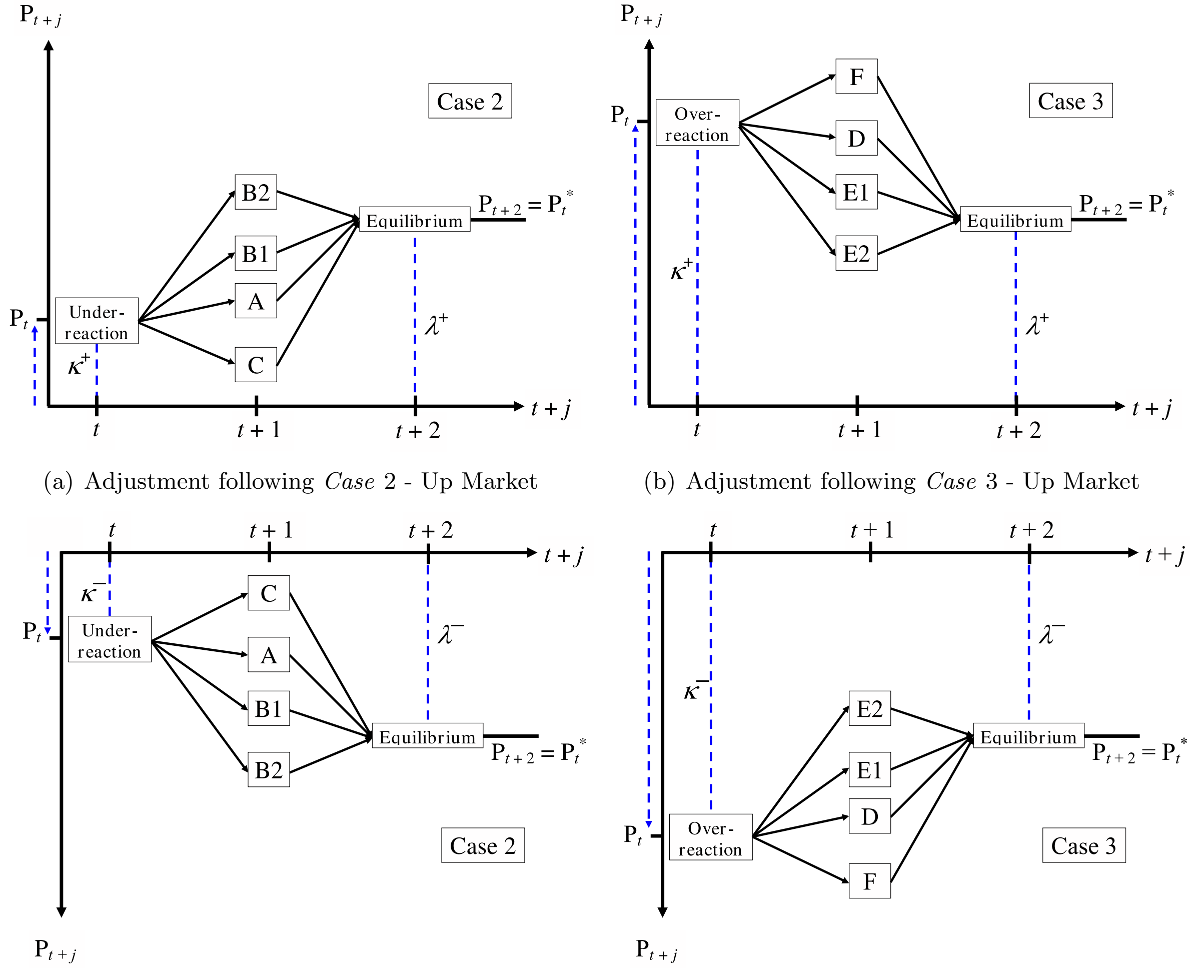
3.4.3 Dynamic Price Discovery

We now examine the dynamic adjustment process following the initial mispricing condition in details. Under the simplifying assumption that the market returns to equilibrium after two periods ($k=2$), we present the alternative adjustment patterns in Figure 2.

Under *Case* 2 (underreaction), Events A and C are more likely to occur in period $t+1$ due to the low speculative demand. On the other hand, under *Case* 3 (overreaction), Events E and F are more likely to occur in period $t+1$ owing to the excess speculative demand. The possible over–adjustment in period $t+1$ could change the market condition from underreaction to overreaction under *Case* 2 (Event $B2$) and from overreaction to underreaction under *Case* 3 (Event $E2$). Importantly, Events $B2$ and F reflect the delayed overshooting under *Cases* 2 and 3, respectively. This is likely to be caused by the trend–chasing behaviour of noise traders (Hong and Stein, 1999).

Abreu and Brunnermeier (2002) show that the fundamentals work as an anchor around which the price can fluctuate. Similarly, in our framework, the long–run pricing impacts of order flow, λ^{+} and λ^{-}, are determined by fundamentals and may form the upper and the lower bounds (see Figure 2). When the prices stay between these bounds, the market underreacts (*Case* 2) and thus the speculative demand is relatively lower. On the other hand, if the prices are outside these bounds, the market overreacts (*Case* 3) and thus the speculative demand is relatively higher. As a result, the mispricing within these bounds is expected to be more persistent than that outside these bounds.

We turn to investigate the implications of the feedback trading strategies. In a usual context, if the price goes up in periods t and $t+1$, then the trading in period $t+1$ is referred to as the positive feedback trading. If the price goes up in period t but goes down in period $t+1$, then the trading in period $t+1$ is referred to as the negative feedback trading. In this regard, the feedback trading strategy can be identified by assessing the correlation between the price movements (return correlation) over two consecutive periods. But, in our dynamic framework, the feedback trading strategy will be determined with regards to the current mispricing condition. Specifically, in absolute terms, if the price is below its equilibrium level (the market is underreacting), the



(a) Adjustment following *Case* 2 - Up Market

(b) Adjustment following *Case* 3 - Up Market

(c) Adjustment following *Case* 2 - Down Market

(d) Adjustment following *Case* 3 - Down Market

*$B1$ and $E1$ represent fast adjustments while $B2$ and $E2$ represent over–adjustments.

Figure 2: The Adjustment Process Following Market Disequilibrium

positive feedback trading will push the price towards its equilibrium whilst the negative feedback trading will pull it further away from the equilibrium level. On the other hand, when the price is above its equilibrium level (the market is overreacting), then the negative feedback trading will bring it downwards to its equilibrium whilst the positive feedback trading will shoot it further away from the equilibrium level.

First, under *Case* 2, if the positive feedback trading dominates in period $t+1$, the price will move towards its equilibrium (Events A or $B1$) or overshoot (Event $B2$). If the negative feedback trading prevails, the price will deviate further from its equilibrium (Event C). Events A, $B1$ and C indicate that the market is still underreacting in period $t+1$ and the positive feedback trading in period $t+2$ will move the price towards its equilibrium. Second, under *Case* 3, the negative feedback trading in period $t+1$ will move the price towards its equilibrium (Events D or $E1$) or over–adjust it (Event $E2$). By contrast, the positive feedback trading in period $t+1$ will cause the price to overshoot (Event F). At D, $E1$ and F, the market is still overreacting and the negative feedback trading in period $t+1$ will bring the market towards equilibrium. These discussions suggest that the positive (negative) feedback trading following the market underreaction (overreaction) generally drives the market towards equilibrium. Finally, Events $E2$ and $B2$ (over–adjustment) could occur in period $t+1$ if noise traders follow the trading strategy of rational traders as discussed in subsections (3.4.1) and (3.4.2). Recall that at $B2$ the mispricing condition changes from underreaction to overreaction, and *vice versa* for $E2$. Hence, it is the negative (positive) feedback trading in period $t+2$ following Event $B2$ ($E2$) in period $t+1$ that will bring the market towards equilibrium.

4 Empirical Application

There is growing evidence that the direct impact of the public information on the exchange rate is relatively small (Hasbrouck, 1991; Evans, 2002; Evans and Lyons, 2002a; b; 2008).[16] Hence, we follow the Evans and Lyons's (2002a) approach by assuming that the public information, ΔR_t, is immediately and directly impounded into the exchange rate, and do not attempt to examine the direct impact of ΔR_t.

4.1 Data and Methodology

We use the Reuters D2000-1 daily dataset as analyzed by Evans and Lyons (2002a; b; 2008). The data contains direct interdealer transactions over a 4–month period from 1 May to 31 August 1996 in eight currency spot markets: German mark, British pound, Japanese yen, Swiss franc, French franc, Belgian franc, Italian lira and Netherlandish guilder, all against the US dollar. These currency markets are henceforth referred to as DEM, GBP, JPY, CHF, FRF, BEF, ITL and NLG, respectively.[17] The exchange rate on day t is the natural logarithm of the spot rate (p_t) which is the last purchase–transaction price before 4PM (GMT). When day t is Monday, the price on day $t-1$ is the previous Friday's. The exchange rates are measured as the prices of the dollar in terms of other currencies such that their increases denote the dollar appreciation. The daily order flow (Δq_t) is measured as the difference between the numbers of the buyer–initiated and the seller–initiated trades in 'thousands' from 4PM on day $t-1$ to 4PM on day t. Dealers buy and sell the dollar for other currencies and negative (positive) order flows signal net sales (purchases) of the dollar. In what follows, we use 'up' and 'down' markets to denote dollar–buying and the dollar–selling pressures, respectively.[18]

Tables 4 and Figure 3 around here

We provide the summary descriptive statistics in the up and the down markets in Table 4. Columns 2–4 report the number of positive, negative and zero order flows, displaying that all the eight currency markets have relatively balanced numbers of positive and negative order flows. The case of zero order flow is negligible and covers less than 2% on average. Columns 9–10 show the total excess trades ($\sum |\Delta q_t|$) and aggregate excess trades ($\sum \Delta q_t$), respectively. DEM has the highest total excess trades, JPY has the largest excess buying orders ($\sum \Delta q_t > 0$) , and CHF has the most excess selling orders ($\sum \Delta q_t < 0$). Figures 3 (a)–(h) plot the exchange rate and cumulative order flow in eight markets, displaying that they move closely together in most markets with the noticeable exceptions being GBP and BEF in which they seem to diverge at the end of the sample period. Of the four heavily–traded markets, the dollar–buying pressure increases towards the end of the sample period in JPY and GBP, but the dollar–selling pressure mounts in DEM and CHF. We also observe that the mark and the Swiss franc display a clear

[16] Evans (2002) and Evans and Lyons (2008) find that public news is rarely the dominant source of exchange rate movement.

[17] About 90% of the global direct interdealer transactions take place through the system. See Evans and Lyons (2002a; b) for further details.

[18] Though we cannot identify the size of individual transactions, the size of the deal is reported as relatively unimportant for pricing in most empirical studies, *e.g.* Bjønnes and Rime (2005), Osler *et al.* (2006), and Reitz *et al.* (2011). Furthermore, Killeen *et al.* (2006) construct the order flows measured both in signed counts and in values for DEM/FRF, and show that the correlation between two order–flow measures over January - April 1998, is remarkably high at 0.98.

appreciating trend against the dollar while the yen exhibits a generally depreciating trend. The pound seems to appreciate despite the mounting dollar–buying pressure in GBP. Furthermore, the exchange rates in DEM, CHF, FRF, BEF and NLG exhibit a quite similar pattern.

The asymmetric ARDL model advanced by SYG combines a nonlinear long–run (cointegrating) relationship with nonlinear error correction and thus represents a natural means of estimating the DAPS model. Consider the asymmetric long–run relationship given by

$$p_t = \lambda^+ q_t^+ + \lambda^- q_t^- + \xi_t, \tag{4.1}$$

where q_t is an $I(1)$ regressor decomposed as $q_t = q_0 + q_t^+ + q_t^-$ with q_t^+ and q_t^- being partial sum processes of positive and negative changes in q_t defined by $q_t^+ = \sum_{j=1}^t \Delta q_j^+ = \sum_{j=1}^t \max(\Delta q_j, 0)$ and $q_t^- = \sum_{j=1}^t \Delta q_j^- = \sum_{j=1}^t \min(\Delta q_j, 0)$, and λ^+, λ^- are the asymmetric long–run parameters. SYG demonstrate that (4.1), can be generalized into the following asymmetric error–correction form:

$$\Delta p_t = \psi p_{t-1} + \theta^+ q_{t-1}^+ + \theta^- q_{t-1}^- + \sum_{j=1}^{p} \pi_j \Delta p_{t-j} + \sum_{j=0}^{q} \left(\varphi_j^+ \Delta q_{t-j}^+ + \varphi_j^- \Delta q_{t-j}^- \right) + e_t \tag{4.2}$$

where both the long–run equilibrium relationship and the dynamic adjustment process are allowed to vary between the two regimes defined by the sign of Δq_t. Since the NARDL model, (4.2), is linear in all the parameters including asymmetric parameters, its estimation can be achieved simply by standard OLS.

In this framework, the nonstandard bounds F–test of the null hypothesis $\psi = \theta^+ = \theta^- = 0$ (no cointegration) can be applied to test for the existence of an asymmetric long–run level relationship (Pesaran *et al.*, 2001). Similarly, (4.2) nests the following special cases: firstly, the long–run symmetry with $\lambda^+ = \lambda^- = \lambda$ where $\lambda^+ = -\theta^+/\psi$ and $\lambda^- = -\theta^-/\psi$; secondly, the short–run symmetry with a strong form of $\varphi_i^+ = \varphi_i^-$ for all $i = 0, ..., q$ or a weak form of $\sum_{j=0}^q \varphi_j^+ = \sum_{j=0}^q \varphi_j^-$;[19] and thirdly, both the long– and the short–run symmetries, in which case (4.2) reduces to the linear ARDL model as considered by Pesaran and Shin (1998) and Pesaran *et al.* (2001). All these restrictions can be easily tested using the standard Wald statistics. Hence, the different forex markets can be categorized into the following four cases: *Case* (i) the pricing impacts of order flows on the exchange rate are asymmetric in both the short– and the long–run; *Case* (ii) the impacts are asymmetric in the short run but symmetric in the long run; *Case* (iii) the impacts are symmetric in the short run but asymmetric in the long run; and *Case* (iv) the impacts are symmetric in both the short– and the long–run.

Finally, the traverse between the short–run disequilibrium and the long–run steady state of the system can be described by the asymmetric cumulative dynamic multipliers:[20]

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial p_{t+j}}{\partial q_t^+}, \; m_h^- = \sum_{j=0}^{h} \frac{\partial p_{t+j}}{\partial q_t^-}, \; h = 0, 1, 2... \tag{4.3}$$

where m_h^+ and m_h^- tend to the respective asymmetric long–run coefficients as the horizon tends to infinity. The ability of the dynamic multipliers to illuminate the traverse between steady states is likely to prove particularly useful in our analysis of the DAPS model, providing insights into the (complicated) dynamic price adjustment as described in Section 3.4.

We then aim to address three main issues. First, what are the typical patterns of the dynamic price adjustment process towards equilibrium after the initial market underreaction or overreaction? A careful examination of this issue can reveal the nature of the market disequilibrium

[19] The contemporaneous impacts of order flows, κ^+ and κ^- in (3.15), can be captured by φ_0^+ and φ_0^- in (4.2).
[20] For further details see SYG.

and the agents' feedback trading strategies.[21] The second issue is whether or not the dynamic adjustment processes are symmetric in up and down markets. There are a growing number of studies providing evidence in favour of the asymmetric impacts of macro news and order flow on the exchange rate (Evans and Lyons, 1999; Andersen *et al.*, 2003). Within the DAPS framework, it is straightforward to evaluate the dynamic price impacts of selling and buying pressures, directly and separately. Finally, we are also interested in the issue of whether the adjustment patterns are similar across different forex markets.

4.2 Static Models

For comparison with most existing studies, we begin with estimating the static models of the following forms:

$$p_t = \lambda q_t + \xi_t, \tag{4.4}$$

$$p_t = \lambda^+ q_t^+ + \lambda^- q_t^- + \xi_t. \tag{4.5}$$

As a prelude to the analysis of the cointegrating relationship between the exchange rate and cumulative order flow, we conduct the augmented Dickey–Fuller unit root test and find that both p_t and q_t are convincingly $I(1)$ in all eight markets. This (unreported) finding is consistent with those reported in Evans and Lyons (2002a) and Berger *et al.* (2008).

The estimation results for the static linear model, (4.4), presented in Table 7 show that the pricing impact of cumulative order flow is significant in all eight markets.[22] Surprisingly, the impact of order flow on the exchange rate is negative in GBP, BEF and ITL. Furthermore, the static linear model also suffers from serial correlation in all eight markets and from incorrect functional form in four. The Engle–Granger (1987) residual–based cointegration test results presented in Table 5 show that the linear cointegrating relationship between the exchange rate and cumulative order flow is confirmed only in NLG.

Tables 5, 6, 7 and 8 around here

Turning to the estimation results for the static asymmetric model, (4.5), reported in Table 8, we find that the coefficients on positive and negative cumulative order flows are significant and correctly signed in most cases. The only exceptions are negative coefficients on positive cumulative order flows in BEF and CHF. The static asymmetric regressions also suffer from serial correlation in all eight markets, and from incorrect functional forms in four. This suggests that the dealers' inventory imbalances are clearly persistent. The Engle–Granger cointegration test results, summarised in Table 6, confirm that there is no (asymmetric) long–run cointegrating relationship between the exchange rate and cumulative order flow with the only exception being NLG.

In summary, the estimation and test results for both static models are generally unsatisfactory. Though we find that the static asymmetric model can provide weak evidence in favour of asymmetric pricing impacts of order flows,[23] the Engle–Granger test results do not provide any evidence in favour of cointegration, which is consistent with the finding of most existing studies, e.g. Berger *et al.* (2008).

[21] Notice that this important issue is rarely analyzed in the literature due to the continuous market–clearing assumption made in most theoretical models, and the empirical failure to find a (symmetric) cointegrating relationship between the exchange rate and order flow.

[22] All coefficients on order flows are multiplied by 100 for clarification as in Evans and Lyons (2002a; b). A constant is also added to all regression equations.

[23] The Wald statistic strongly rejects the null of $\lambda^+ = \lambda^-$ in (4.5) in all eight markets.

4.3 Dynamic Models

We begin with our proposed DAPS model, which does not impose any symmetry restrictions in the short– and the long–run,[24] and test the null hypotheses of no cointegration, short– and long–run symmetries as described in subsection 4.1. We then select the most preferred specification for each of the eight markets.

The estimation and test results for (3.15), presented in Table 9, clearly demonstrate that the long–run pricing impacts of order flows are correctly signed and statistically significant in almost all markets. The dynamic asymmetric regressions do not display any residual serial correlation in all eight markets but there is weak evidence of heteroskedasticity in four markets. Notice that the adjusted R^2s $(\bar{R}^2)$ range between 0.26 and 0.76. In particular, the $\bar{R}^2$s in DEM and JPY are 0.76 and 0.66, respectively, which are remarkably higher than the corresponding $\bar{R}^2$s of 0.64 and 0.46 reported in Evans and Lyons (2002b). Moreover, the $\bar{R}^2$s for other forex markets are predominantly higher than those reported in Evans and Lyons (2002a). This improvement clearly demonstrates that the static return regressions employed in Evans and Lyons (2002a; b) suffer from omitting the significant error–correction term.

Table 9 around here

We now examine the test results. First, we find that the F–statistics (F_{PSS}) reported in Table 9, strongly reject the null of no cointegration in seven markets at the 5% significance level and in BEF at the 10% level. This confirms that an asymmetric long–run cointegrating relationship between the exchange rate and cumulative order flow exists in all markets. Second, it is quite remarkable to find from Table 9 that the Wald statistics, denoted W_{SR} and W_{LR}, reject both the nulls of short–run and long–run symmetries in the price impacts of positive and negative order flows for almost all markets. The exceptions are: the long–run symmetry is not rejected in CHF and NLG while the short–run symmetry is not rejected in GBP and FRF. Based on these test results, we may categorize the eight markets as follows: DEM, JPY, BEF and ITL belong to *Case* (i); CHF and NLG to *Case* (ii); GBP and FRF to *Case* (iii); and none to *Case* (iv).

For comparison purpose, we also provide the estimation and test results for the dynamic symmetric model. The results reported in Table 10 show that a linear cointegrating relationship is confirmed only in CHF, FRF and NLG. Importantly, the estimated long–run pricing impacts of order flows are quite misleading. In particular, they become insignificant in three major markets (DEM, JPY and GBP) and even incorrectly negative in DEM and GBP. Furthermore, the error–correction coefficients, measuring the speed of adjustment towards equilibrium, are all significantly smaller than those obtained from the dynamic asymmetric regressions.[25] Therefore, the poor and misleading results of the dynamic linear model are mainly attributed to the imposition of invalid symmetry restrictions in the short– and the long–run.

Table 10 around here

Next, we examine the asymmetric pricing impacts of positive and negative order flows on the exchange rate from Table 9. We find that the long–run coefficients on negative order flows (associated with down market) are greater than those on positive ones (associated with up market) in seven markets with the exception being NLG. Such differentials are statistically

[24] We follow the general–to–specific approach recommended by SYG and select the final lag orders of the asymmetric ARDL specification, (4.2), by starting with $p_{max} = q_{max} = 14$ and dropping all insignificant stationary regressors sequentially. Our choice of the maximum lag order is justified by previous studies (Evans and Lyons, 2005, 2006; Reitz *et al.*, 2011), suggesting that information is slowly embedded into the exchange rate.

[25] Adjustment speeds for JPY and GBP estimated from dynamic symmetric regressions are about 5 and 7 times slower than those from dynamic asymmetric regressions. Surprisingly, the error–correction coefficient is positive for DEM when using dynamic symmetric regression. Only for CHF where the null of the long–run symmetry is not rejected, adjustment coefficients from both models are relatively similar.

significant in six markets with the exception being CHF. By construction of our DAPS model, (3.15), the asymmetry in the long run (equilibrium) price impacts of positive and negative order flows implies the asymmetry in their contemporaneous price impacts. From Table 9, the coefficients on Δq_t^- are greater than those on Δq_t^+ in all markets,[26] consistent with the prediction of our theoretical model. Finally, the speed of adjustment towards equilibrium under the dynamic asymmetric model varies across markets. GBP exhibits the fastest adjustment speed, followed by NLG, FRF and JPY. Such variation may reflect the different liquidity levels across the eight markets, and the deviations from equilibrium are expected to be corrected relatively more quickly in more liquid markets than in less liquid ones.

In sum, we find that both the short– and the long–run pricing impacts of negative order flow are significantly greater than those of positive one. Recall that the asymmetric pricing impacts of order flows in the DAPS model stem mainly from the asymmetric risk aversion levels of traders in up and down markets. Hence, our findings indicate that traders are generally more risk–averse in down market and respond more strongly to selling pressure. Strong evidence of asymmetric responses of traders together with the varying speeds of adjustment clearly suggests that the price discovery processes are quite complicated and heterogeneous across different currency markets, which we will investigate below.

4.4 Price Discovery Process

We investigate the price discovery process through the dynamic multiplier analysis which enables us to examine how the price evolves towards equilibrium with respect to the unit impacts of the daily excess buying and selling orders (measured in thousands).[27] We display the results under *Case* (i) for all markets in Figure 4 and those under the *Cases* selected by the testing results in Figure 5. The test results in subsection 4.3 suggest that *Case* (ii) be selected for CHF and NLG and *Case* (iii) for GBP and FRF. The price discovery processes for CHF and NLG are quite similar under *Case* (i) and *Case* (ii) as is clear in Figures 4 and 5. Furthermore, the estimation results of the DAPS model show that the adjustment processes towards equilibrium are quite different under up and down markets in GBP and FRF. Hence, without loss of generality, we will focus on *Case* (i) for all eight markets.[28]

Figures 4 and 5 around here

A careful inspection of Figure 4 suggests several stylised findings. First, the net effects - the differences between the price impacts of the unit changes in positive and negative order flows - are mostly negative over all horizons. This implies that the impact of selling pressure is stronger than that of buying pressure of the same magnitude, thus supporting that traders are likely to be more risk–averse in the down market. In particular, the long–run price impacts of negative order flows are about 1.2%, 3.7%, 1.8%, 1.9%, 60%, and 10% larger than those of positive order flows in DEM, GBP, JPY, FRF, BEF and ITL, respectively. The differentials are relatively negligible only in CHF and NLG. Second, we find that mispricing is not eliminated immediately but also persistent in all eight markets. The degree of persistence varies across markets depending on

[26] Both coefficients are statistically insignificant in BEF.

[27] The impacts of negative order flow are multiplied by -1 to highlight the difference through the net effects.

[28] Most microstructure models of the exchange rate belong to *Case* (iv) where the short– and long–run symmetry restrictions are imposed (e.g. Evans and Lyons, 2002a; b, 2008; Bjønnes and Rime, 2005; Berger *et al.*, 2008; and Reitz *et al.*, 2011). Considering that both symmetry restrictions are strongly rejected in most markets, the symmetric dynamic multiplier effects are likely to be misleading in practice. In particular, we find that the pricing impact of order flow under *Case* (iv) is not theory–consistent (negative) in GBP and BEF, and even diverges infinitely in DEM and ITL. Moreover, the separate imposition of the invalid long–run symmetry under *Case* (ii) or the short–run symmetry under *Case* (iii) is also likely to result in misleading pricing impacts. This is demonstrated by the long–run divergence under *Case* in DEM and ITL (ii), and the counter–intuitive price movements under *Case* (ii) in GBP and under *Case* (iii) in BEF. All these results are unreported but will be available upon request.

the nature of the disequilibrium condition, under– or overreaction. Importantly, the persistent mispricing clearly indicates the limits of arbitrage as discussed in Abreu and Brunnermeier (2002, 2003), DeLong *et al.* (1990a; b) and Shleifer and Vishny (1997).

Third, we observe two typical patterns of the price discovery process in the presence of short–term market disequilibrium. Specifically, the price discovery process following market underreaction is generally characterised by a sequence of relatively small and gradual adjustments towards equilibrium. Markets exhibiting this adjustment pattern, denoted Group 1, include DEM, CHF, BEF and ITL.[29] This pattern resembles Events A and C in Figure 2. As discussed in subsection 3.2, if the underreacting behaviour persists, it may curb market liquidity (decreasing habit level), resulting in a persistent adjustment process towards equilibrium. Indeed, we find that the error correction coefficients are relatively small at -0.1, -0.08, -0.16 and -0.28 for DEM, CHF, BEF and ITL, respectively (see Table 9). Moreover, the gradual adjustment towards equilibrium observed in Group 1 may suggest that overall the positive feedback trading by rational speculators dominates, slowly removing mispricing and pushing the price towards its equilibrium as discussed in subsection 3.4.1. Meanwhile, the detractions observed during the adjustment process in Group 1 reflect the negative feedback trading of noise traders (Event C).

By contrast, after the initial overreaction the price discovery process is typified by delayed overshooting, followed by a volatile but faster adjustment episode. GBP, JPY, FRF and NLG (Group 2) clearly display such short–term instability which is likely to be explained by the excess speculative demand (increasing habit level) associated with the market overreaction. This finding is consistent with the discussion in Tobin (1978) and Summers and Summers (1989) that the excess speculative demand may cause market instability. Notice from Figure 2 that both the delayed overshooting and the over–adjusting Events ($E2$ and F) are clearly observed for Group 2. These events are likely to result from the trend–chasing behaviour of (momentum) noise traders as analysed in Hong and Stein (1999) and DeLong *et al.* (1990b). Overall, it is the negative feedback trading of rational traders that brings overreacted prices towards equilibrium. Given the excess speculative demand under the overreacting condition, traders can trade in and out of positions relatively easily, and thus they may take larger arbitrage positions than they do in a liquidity–constrained market. Indeed, the error correction coefficients are at -0.44, -0.29, -0.30, -0.40 for GBP, JPY, FRF and NLG, respectively (see Table 9), supporting our expectation that the adjustment speeds of Group 2 are relatively faster than those of Group 1.

Finally, the long–run pricing impacts of positive and negative order flows provide the upper and the lower bounds, respectively, around which the price fluctuates. Recall that the deviation outside these bounds indicates market overreaction and a relatively high speculative demand level. On the other hand, the deviation within these bounds signals market underreaction and a relatively low speculative demand level. The different levels of speculative demand is likely to imply the different adjustment speeds inside and outside these bounds. In fact, we find that the deviations outside these bounds are quickly corrected but the deviations within these two bounds tend to be persistent, consistent with our theoretical discussions in subsection 3.4.3.

5 Concluding Remarks

Based on the portfolio shifts framework of Evans and Lyons (2002a; b), we develop a more general microstructure model of exchange rate determination. Importantly, our model allows for persistent mispricing and asymmetric pricing impacts of order flow on the exchange rate. Using the Reuters D2000–1 trading dataset for eight currency markets, we find strong evidence of a nonlinear cointegrating relationship between the exchange rate and order flow. In particular, our

[29] The insignificant contemporaneous price impact and the awkward short–term price movements in BEF may reflect the fact that it is a sub–market and depends more on the pricing information from the large and leading market such as DEM than on its own. Evans and Lyons (2002a) suggest that the price in BEF is strongly affected by order flows in two dominant regional markets, DEM and CHF.

results show that the pricing impact of dollar–selling pressure is overwhelmingly stronger than that of dollar–buying pressure. Such asymmetric impacts support our assumption that traders are more risk averse in unfavourable markets (selling pressure). Given the growing evidence that the major impact of macro news on the exchange rate is channeled indirectly through the trading process (Evans and Lyons, 2005; 2008; Love and Payne, 2008), our finding indicates that traders seem to respond more strongly to bad news, as also discussed in Andersen *et al.* (2003). Thus, the failure to account for such asymmetric relationship between the exchange rate and fundamentals may be one of the reasons behind the poor performance of macro exchange rate models. Moreover, the significant difference between the short– and long–run pricing impacts of order flow clearly indicates short–term market over– or underreactions, further suggesting that all agents are not necessarily fully rational and arbitrage is limited.

Next, we document that the price discovery process following market underreactions generally consists of small and gradual adjustments. This reflects the dominance of the positive feedback trading by rational traders, pushing the market towards equilibrium. By contrast, the price discovery process after market overreactions displays overshooting and volatile adjustments. We argue that such volatile episode is probably attributed to the expanded speculative demand caused by market overreactions. In particular, the trend–chasing feedback trading of noise traders following market overreactions could destabilise the market, resulting in delayed overshooting impacts and often over–adjustments (DeLong *et al.*, 1990; Hong and Stein, 1999). Hence, depending on market condition, feedback trading strategies can generate stable or turbulent episodes of adjustment as argued by Tambakis (2009). The instability in liquid market is also supported by the traditional economic view of liquidity (Keynes, 1935; Tobin, 1978). However, such instability only exist in the short run and deviations following market overreactions are corrected faster than those following underreactions. In general, our empirical findings support our proposed DAPS model.

References

Abel, A. B. (1999). Risk premia and term premia in general equilibrium. *Journal of Monetary Economics*, *43*(1), 3-33.

Abreu, D., & Brunnermeier, M. K. (2002). Synchronization risk and delayed arbitrage. *Journal of Financial Economics*, *66*(2-3), 341 - 360.

Abreu, D., & Brunnermeier, M. K. (2003). Bubbles and crashes. *Econometrica*, *71*(1), 173-204.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2003). Micro effects of macro announcements: Real time price discovery in foreign exchange. *American Economic Review*, *93*, 38-62.

Bacchetta, P., & Wincoop, E. v. (2006). Can information heterogeneity explain the exchange rate determination puzzle? *American Economic Review*, *96*(3), 552-576.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*, 307-343.

Berger, D. W., Chaboud, A. P., Chernenko, S. V., Howorka, E., & Wright, J. (2008). Order flow and exchange rate dynamics in electronic brokerage system data. *Journal of International Economics*, *75*(1), 93-109.

Bjonnes, G. H., & Rime, D. (2005). Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics*, *75*(3), 571-605.

Bloom, H. S., & Price, H. D. (1975). Voter response to short-run economic conditions: The asymmetric effect of prosperity and recession. *American Political Science Review*, *69*, 1240-1254.

Bowman, D., Minehart, D., & Rabin, M. (1999). Loss aversion in a consumption-savings model. *Journal of Economic Behavior and Organization*, *38*, 155178.

Boyer, M. M., & Norden, S. van. (2006). Exchange rates and order flow in the long run. *Finance Research Letters*, *3*(4), 235-243.

Brandt, M. W., & Wang, K. Q. (2003). Time-varying risk aversion and unexpected inflation. *Journal of Monetary Economics*, *50*(7), 1457-1498.

Cai, C. X., Faff, R., & Shin, Y. (2011). *Limited arbitrage and noise momentum: Theory and evidence.* (Unpublished manuscript, University of Leeds)

Campbell, J. Y., & Cochrane, J. (1999). By force of habit: a consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, *107*(2), 205-251.

Campbell, J. Y., & Kyle, A. S. (1993). Smart money, noise trading and stock price behaviour. *Review of Economic Studies*, *60*(1), 1-34.

Chapman, D. A. (1998). Habit formation and aggregate consumption. *Econometrica*, *66*(5), 1223-1230.

Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics*, *65*(1), 111-130.

Cohen, B. H., & Shin, H. S. (2003). *Positive feedback trading under stress: Evidence from the us treasury securities market* (Working Paper No. 122). BIS.

Danelsson, J., & Love, R. (2006). Feedback trading. *International Journal of Finance & Economics*, *11*(1), 35-53.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *Journal of Finance*, *53*, 1839-1885.

DeLong, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990a). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703-738.

DeLong, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990b). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, *45*(2), 379-95.

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, *55*(2), 251-76.

Evans, M. D. D. (2002). Fx trading and exchange rate dynamics. *Journal of Finance*, *57*(6), 2405-2447.

Evans, M. D. D., & Lyons, R. K. (1999). *Order flow and exchange rate dynamics* (Working Paper No. 7317). National Bureau of Economic Research.

Evans, M. D. D., & Lyons, R. K. (2002a). Informational integration and fx trading. *Journal of International Money and Finance*, *21*(6), 807-831.

Evans, M. D. D., & Lyons, R. K. (2002b). Order flow and exchange rate dynamics. *Journal of Political Economy*, *110*(1), 170-180.

Evans, M. D. D., & Lyons, R. K. (2002c). Time-varying liquidity in foreign exchange. *Journal of Monetary Economics*, *49*(5), 1025-1051.

Evans, M. D. D., & Lyons, R. K. (2005). Do currency markets absorb news quickly? *Journal of International Money and Finance*, *24*(2), 197-217.

Evans, M. D. D., & Lyons, R. K. (2006). Understanding order flow. *International Journal of Finance & Economics*, *11*(1), 3-23.

Evans, M. D. D., & Lyons, R. K. (2008). How is macro news transmitted to exchange rates? *Journal of Financial Economics*, *88*(1), 26-50.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*, 283-306.

Figlewski, S. (1979). Subjective information and market efficiency in a betting market. *Journal of Political Economy*, *87*(1), 75-88.

Flood, R. P., & Taylor, M. P. (1996). Exchange rate economics: What's wrong with the conventional macro approach? In J. Frankel, G. Galli, & A. Giovannini (Eds.), *The microstructure of foreign exchange markets* (p. 261-302). National Bureau of Economic Research, Inc.

Frankel, J. A., & Rose, A. K. (1995). Empirical research on nominal exchange rates. In G. M. Grossman & K. Rogoff (Eds.), *Handbook of international economics* (Vol. 3, p. 1689-1729). Elsevier.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance*, *46*(1), 179-207.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, *54*(6), 2143-2184.

Ito, T., Lyons, R. K., & Melvin, M. T. (1998). Is there private information in the fx market? the tokyo experiment. *Journal of Finance*, *53*(3), 1111-1130.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). The endownment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, *5*, 193-206.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263-292.

Keynes, J. M. (1935). *The general theory of employment, interest and money.* Palgrave Macmillan.

Killeen, W. P., Lyons, R. K., & Moore, M. J. (2006). Fixed versus flexible: Lessons from ems order flow. *Journal of International Money and Finance*, *25*(4), 551-579.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, *53*(6), 1315-35.

Larson, S., & Madura, J. (2001). Overreaction and underreaction in the foreign exchange market. *Global Finance Journal*, *12*, 153-177(25).

Lau, R. R. (1985). Two explanations for negativity effects in political behavior. *American Journal of Political Science*, *29*, 119-138.

Love, R., & Payne, R. (2008). Macroeconomic news, order flows, and exchange rates. *Journal of Financial and Quantitative Analysis*, *43*(02), 467-488.

Luo, J. (2001). *Market conditions, order flow and exchange rates determination* (Working Paper). London School of Economics.

Lyons, R. K. (1997). A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, *42*(3-4), 275-298.

Lyons, R. K. (2001). *The microstructure approach to exchange rates.* MIT Press: Cambridge, MA.

Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies : Do they fit out of sample? *Journal of International Economics*, *14*(1-2), 3-24.

Osler, C., Mende, A., & Menkhoff, L. (2006). *Price discovery in currency markets* (Discussion Paper No. 351). Leibniz Universitaet Hannover.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289-326.

Reitz, S., Schmidt, M., & Taylor, M. P. (2011). End-user order flow and exchange rate dynamics - a dealer's perspective. *European Journal of Finance*, *17*, 153 - 168.

Rime, D. (2001). *Us exchange rates and currency flows* (SIFR Research Report Series No. 4). Swedish Institute for Financial Research.

Rime, D., Sarno, L., & Sojli, E. (2010). Exchange rate forecasting, order flow and macroeconomic information. *Journal of International Economics*, *80*, 72-88.

Sager, M. J., & Taylor, M. P. (2006). Under the microscope: the structure of the foreign exchange market. *International Journal of Finance and Economics*, *11*(1), 81-95.

Samuelson, P. A. (1989). A case at last for age-phased reduction in equity. In *Proceedings of the national academy of sciences* (Vol. 86, p. 9048-9051).

Sarno, L., & Taylor, M. P. (2001). *The microstructure of the foreign-exchange market: A selective survey of the literature* (Princeton Studies in International Economics No. 89). Department of Economics, Princeton University.

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2009). *Modelling asymmetric cointegration and* *dynamic multipliers in an ardl framework* (Working Paper). Leeds University Business School.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*(1), 35-55.

Skowronski, J. J., & Carlston, D. E. (1989). Negativity and extremity biases in impression formation: A review of explanations. *Psychological Bulletin*, *105*, 131 - 142.

Soroka, S. N. (2006). Good news and bad news: Asymmetric responses to economic information. *Journal of Politics*, *68*, 372-385.

Tambakis, D. N. (2009). Feedback trading and intermittent market turbulence. *Quantitative Finance*, *9*(4), 477-489.

Tobin, J. (1978). A proposal for international monetary reform. *Eastern Economic Journal*, *4*(3-4), 153-159.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, *106*, 1039-1061.

Vonk, R. (1996). Negativity and potency effects in impression formation. *European Journal of Social Psychology*, *26*, 851-865.

Wang, J., & Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. *Journal of International Financial Markets, Institutions and Money*, *19*(4), 597-615.

Appendix: Tables and Figures

Mkt.	# Δq_t^+	# Δq_t^-	# Δq_t^0	$\overline{\Delta q}^+$	$\overline{\Delta q}^-$	$\sum \Delta q_t^+$	$\sum \Delta q_t^-$	$\sum \lvert\Delta q_t\rvert$	$\sum \Delta q_t$	$\sum \Delta p_t$
DEM	39	43	0	110.9	-101.0	4326	-4343	8669	-17	-0.037
GBP	50	31	1	43.2	-34.9	2162	-1082	3244	1080	-0.043
JPY	55	27	0	89.2	-72.4	4907	-1954	6861	2953	0.033
CHF	36	46	0	43.5	-65.5	1565	-3011	4576	-1446	-0.041
FRF	41	40	1	21.8	-23.0	894	-919	1813	-25	-0.022
BEF	55	24	3	7.3	-6.3	403	-151	554	252	-0.035
ITL	43	37	2	12.3	-11.4	529	-421	950	108	-0.035
NLG	30	46	6	4.4	-6.2	132	-287	419	-155	-0.036

*'#' denote the number of observations. Δq_t^0 denotes $\Delta q_t = 0$.

Table 4: Summary Statistics of the Reuters D2000–1 Dataset

Lag order	DEM	GBP	JPY	CHF	FRF	BEF	ITL	NLG
0	0.234	-1.881	-1.780	-1.320	-3.256	-2.339	-2.704	-4.009
1	0.194	-1.999	-1.751	-1.245	-3.331	-2.583	-2.710	-4.195
2	0.209	-2.153	-1.802	-1.239	-2.987	-2.432	-3.185	-4.101
3	0.519	-2.118	-1.606	-1.233	-2.992	-2.235	-3.065	-3.647
4	0.301	-1.782	-1.723	-1.361	-2.898	-1.991	-2.843	-3.518
5	0.347	-1.814	-1.712	-1.363	-2.869	-1.895	-2.615	-3.065

*The EGDF regressions include an intercept but not a trend. The 95% critical value for the EGDF statistic is -3.419.

Table 5: Engle–Granger Cointegration Test Results for the Static Symmetric Model

Lag order	DEM	GBP	JPY	CHF	FRF	BEF	ITL	NLG
0	-1.846	-3.820	-2.923	-2.501	-2.888	-2.699	-3.964	-4.255
1	-1.954	-3.211	-2.526	-2.534	-3.032	-3.017	-3.285	-4.522
2	-1.667	-3.518	-2.594	-2.549	-2.308	-2.897	-3.372	-4.491
3	-1.469	-3.861	-2.375	-2.505	-2.316	-2.736	-3.414	-4.077
4	-1.580	-3.342	-2.942	-2.507	-2.041	-2.514	-3.064	-4.069
5	-1.570	-3.530	-3.028	-2.454	-2.009	-2.448	-2.856	-3.449

*The EGDF regressions include an intercept but not a trend. The 95% critical value for the EGDF statistic is -3.857

Table 6: Engle–Granger Cointegration Test Results for the Static Asymmetric Model

Regressor	DEM		GBP		JPY		CHF	
	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio
q_t	3.50	11.00[.000]	-1.30	-5.081[.000]	1.20	10.33[.000]	3.20	9.223[.000]
Constant	0.42	308.2[.000]	-0.43	-274.7[.000]	4.66	2230.[.000]	0.25	60.21[.000]
Adj. R^2	0.600		0.237		0.570		0.512	
χ^2_{SC}	74.092[.000]		63.950[.000]		66.644[.000]		73.522[.000]	
χ^2_{FF}	.44256[.506]		.28204[.595]		9.3695[.002]		53.639[.000]	
χ^2_{N}	12.254[.002]		6.1213[.047]		4.5742[.102]		7.3636[.025]	
χ^2_{HE}	.01214[.912]		18.492[.000]		3.3224[.068]		.35658[.550]	

(a) DEM, GBP, JPY, CHF

Regressor	FRF		BEF		ITL		NLG	
	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio
q_t	9.30	18.36[.000]	-19.10	-13.09[.000]	-15.10	-8.66[.000]	22.60	24.23[.000]
Constant	1.63	1982.[.000]	3.45	2152.[.000]	7.34	6798.[.000]	0.54	653.7[.000]
Adj. R^2	0.809		0.681		0.481		0.880	
χ^2_{SC}	59.745[.000]		62.148[.000]		54.247[.000]		39.935[.000]	
χ^2_{FF}	7.1684[.007]		7.0055[.008]		2.1256[.145]		.20973[.647]	
χ^2_{N}	3.5194[.172]		6.5305[.038]		1.4867[.476]		2.5334[.282]	
χ^2_{HE}	2.8965[.089]		1.8340[.176]		1.3314[.249]		1.0626[.303]	

*[.] is the p-value; χ^2_{SC} is the Lagrange Multiplier statistic for testing the null of no serial correlation; χ^2_{FF} is the Ramsey's RESET test statistic; χ^2_{N} is the Jarque–Bera statistic for testing the null of normal errors; χ^2_{HE} is the statistic for testing the null of no heteroskedasticity.

(b) FRF, BEF, ITL, NLG

Table 7: Estimation Results of the Static Symmetric Model

Regressor	DEM		GBP		JPY		CHF	
	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio
q_t^+	1.60	7.038[.000]	0.50	4.000[.000]	2.00	21.30[.000]	-1.80	-1.69[.094]
q_t^-	2.40	11.89[.000]	4.10	14.52[.000]	3.50	17.73[.000]	1.00	1.763[.082]
Constant	0.43	331.0[.000]	-0.41	-410.[.000]	4.66	3840.[.000]	0.24	65.60[.000]
Adj. R^2	0.870		0.881		0.854		0.620	
χ^2_{SC}	67.770[.000]		36.379[.000]		47.625[.000]		67.416[.000]	
χ^2_{FF}	32.618[.000]		.83368[.361]		9.0461[.003]		52.874[.000]	
χ^2_N	4.0635[.131]		.25518[.880]		3.6603[.160]		2.2071[.332]	
χ^2_{HE}	1.0806[.299]		.75396[.385]		0.0007[.978]		7.5936[.006]	
WALD	165.05[.000]		429.31[.000]		154.50[.000]		23.314[.000]	

(a) DEM, GBP, JPY, CHF

Regressor	FRF		BEF		ITL		NLG	
	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio	Coefficient	t–ratio
q_t^+	5.80	11.36[.000]	-6.60	-1.75[.083]	0.24	.2797[.780]	38.60	9.128[.000]
q_t^-	7.80	20.16[.000]	11.60	1.318[.191]	8.60	7.556[.000]	27.70	17.49[.000]
Constant	1.64	1100.[.000]	3.46	2097.[.000]	7.36	10684.[.000]	0.53	334.8[.000]
Adj. R^2	0.906		0.721		0.939		0.898	
χ^2_{SC}	50.724[.000]		62.317[.000]		34.044[.000]		29.863[.000]	
χ^2_{FF}	1.1769[.278]		4.9194[.027]		5.0052[.025]		.02868[.866]	
χ^2_N	5.5652[.062]		4.3073[.116]		5.3303[.070]		1.6195[.445]	
χ^2_{HE}	10.921[.001]		.77754[.378]		.19059[.662]		.98143[.322]	
WALD	83.863[.000]		12.434[.000]		594.14[.000]		15.023[.000]	

*WALD stands for the Wald statistic for testing the null hypothesis, $\lambda^+ = \lambda^-$, which follows χ^2 distribution under the null. See also footnotes to Table 7.

(b) FRF, BEF, ITL, NLG

Table 8: Estimation Results of the Static Asymmetric Model

DEM			GBP			JPY			CHF		
Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio
p_{t-1}	-0.10	-1.92[.059]	p_{t-1}	-0.44	-4.43[.000]	p_{t-1}	-0.29	-3.74[.000]	p_{t-1}	-0.08	-2.26 [.028]
q^+_{t-1}	0.35	2.92[.005]	q^+_{t-1}	0.34	2.78[.007]	q^+_{t-1}	0.63	4.00[.000]	q^+_{t-1}	0.55	1.74[.087]
q^-_{t-1}	0.47	3.15[.003]	q^-_{t-1}	1.99	4.20[.000]	q^-_{t-1}	1.17	4.11[.000]	q^-_{t-1}	0.6	3.67[.001]
L_{q^+}	3.32	2.28[.026]	L_q^+	0.78	3.05[.003]	L_q^+	2.12	7.57[.000]	L_q^+	6.69	1.21[.230]
L_{q^-}	4.44	3.19[.002]	L_q^-	4.52	8.40[.000]	L_q^-	3.95	7.91[.000]	L_q^-	7.35	2.25[.027]
Δp_{t-2}	-12.78	-2.00[.050]	Δq_t^+	2.71	2.65[.010]	Δp_{t-2}	18.08	1.82[.074]	Δp_{t-1}	-20.94	-2.92[.005]
Δp_{t-3}	-28.84	-3.06[.003]	Δq_t^-	4.25	2.97[.004]	Δp_{t-4}	13.78	1.74[.086]	Δp_{t-10}	18.25	2.42[.019]
Δq_t^+	2.23	6.79[.000]	Δq^-_{t-1}	3.62	2.51[.014]	Δp_{t-6}	21.62	1.98[.053]	Δp_{t-12}	31.38	3.07[.003]
Δq^+_{t-6}	-1.25	-3.68[.001]	Δq^-_{t-2}	-3.10	-2.17[.033]	Δq_t^+	2.12	4.14[.000]	Δq_t^+	2.95	1.96[.055]
Δq^+_{t-12}	0.75	1.96[.055]	Δq^-_{t-6}	-2.51	-2.19[.032]	Δq^+_{t-5}	1.74	3.44[.001]	Δq^+_{t-3}	-2.71	-2.04[.045]
Δq^+_{t-14}	-0.68	-1.67[.100]	Δq^-_{t-8}	-2.78	-2.24[.028]	Δq^+_{t-11}	-2.10	-4.14[.000]	Δq^+_{t-8}	-3.19	-2.41[.019]
Δq_t^-	2.70	7.51[.000]				Δq_t^-	5.53	7.27[.000]	Δq^+_{t-10}	-3.80	-2.60[.012]
Δq^-_{t-3}	0.94	2.32[.024]				Δq^-_{t-2}	-2.68	-2.93[.005]	Δq_t^-	8.43	10.53[.000]
Δq^-_{t-7}	-0.51	-1.92[.059]				Δq^-_{t-6}	-2.61	-2.77[.008]	Δq^-_{t-12}	-1.69	-1.83[.072]
Δq^-_{t-13}	0.63	2.32[.024]				Δq^-_{t-7}	-1.56	-2.36[.022]			
						Δq^-_{t-14}	-1.68	-2.45[.017]			
Const.	0.04	2.00[.050]	Const.	-0.18	-4.47[.000]	Const.	1.38	3.73[.000]	Const.	0.02	2.99[.004]
Adj. R^2	0.765		Adj. R^2	0.449		Adj. R^2	0.668		Adj. R^2	0.730	
χ^2_{SC}	1.9327[.164]		χ^2_{SC}	.29421[.588]		χ^2_{SC}	.34494[.557]		χ^2_{SC}	.39673[.529]	
χ^2_{FF}	9.1477[.002]		χ^2_{FF}	.44313[.506]		χ^2_{FF}	.02074[.885]		χ^2_{FF}	4.2746[.039]	
χ^2_{N}	3.7830[.151]		χ^2_{N}	13.530[.001]		χ^2_{N}	.37789[.828]		χ^2_{N}	.27810[.870]	
χ^2_{HE}	5.7783[.016]		χ^2_{HE}	1.8715[.171]		χ^2_{HE}	1.9015[.168]		χ^2_{HE}	23.1068[.000]	
F_{PSS}	4.911		F_{PSS}	6.822		F_{PSS}	5.659		F_{PSS}	5.497	
W_{LR}	16.9480[.000]		W_{LR}	127.9400[.000]		W_{LR}	47.854[.000]		W_{LR}	.0725[.788]	
W_{SR}	7.9305[.005]		W_{SR}	1.3842[.239]		W_{SR}	5.9267[.015]		W_{SR}	14.5759[.000]	

(a) DEM, GBP, JPY, CHF

continued overleaf...

...continued from previous page

FRF			BEF			ITL			NLG		
Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio
p_{t-1}	-0.30	-3.90[.000]	p_{t-1}	-0.16	-3.17[.002]	p_{t-1}	-0.28	-3.31[.002]	p_{t-1}	-0.40	-3.89[.000]
q^+_{t-1}	1.39	1.69[.095]	q^+_{t-1}	3.34	1.72[.090]	q^+_{t-1}	2.35	3.17[.002]	q^+_{t-1}	12.35	1.64[.105]
q^-_{t-1}	1.97	2.58[.012]	q^-_{t-1}	13.54	2.71[.009]	q^-_{t-1}	5.41	4.54[.000]	q^-_{t-1}	10.03	2.84[.006]
L_{q^+}	4.59	2.33[.022]	L^+_q	19.88	1.50[.138]	L^+_q	8.29	2.24[.028]	L^+_q	30.81	2.03[.046]
L_{q^-}	6.51	5.31[.000]	L^-_q	80.42	2.56[.013]	L^-_q	19.09	3.95[.000]	L^-_q	25.02	5.40[.000]
Δq^+_t	5.47	1.96[.054]	Δp_{t-5}	30.26	2.73[.009]	Δp_{t-1}	-25.20	-2.76[.008]	Δp_{t-1}	22.67	1.87[.066]
Δq^+_{t-5}	1.88	1.04[.298]	Δq^+_{t-3}	-26.05	-3.27[.002]	Δp_{t-8}	26.28	2.61[.011]	Δp_{t-6}	-13.36	-1.23[.220]
Δq^+_{t-6}	3.28	1.85[.068]	Δq^+_{t-6}	25.42	2.55[.014]	Δp_{t-9}	28.59	2.82[.006]	Δq^+_{t-10}	-24.36	-1.79[.077]
Δq^-_t	11.85	6.52[.000]	Δq^+_{t-9}	13.95	1.63[.109]	Δq^+_t	10.80	4.17[.000]	Δq^-_t	25.11	2.61[.011]
Δq^-_{t-9}	4.20	2.68[.009]	Δq^+_{t-11}	17.94	1.67[.100]	Δq^+_{t-3}	-4.13	-1.70[.095]	Δq^-_{t-5}	25.45	2.73[.008]
			Δq^+_{t-14}	-21.78	-2.67[.010]	Δq^-_t	12.47	4.96[.000]	Δq^-_{t-11}	16.12	1.70[.094]
			Δq^-_{t-1}	-35.01	-3.08[.003]	Δq^-_{t-4}	-4.71	-1.98[.052]			
			Δq^-_{t-4}	-27.38	-2.27[.027]	Δq^-_{t-5}	-6.22	-2.59[.012]			
			Δq^-_{t-6}	21.53	1.72[.090]	Δq^-_{t-6}	-8.84	-3.66[.001]			
			Δq^-_{t-11}	-57.72	-3.81[.000]	Δq^-_{t-8}	-5.30	-1.88[.065]			
			Δq^-_{t-12}	-38.28	-3.19[.002]	Δq^-_{t-9}	-8.32	-2.80[.007]			
Const.	0.49	3.92[.000]	Const.	0.58	3.16[.003]	Const.	2.08	3.31[.002]	Const.	0.21	3.96[.000]
Adj. R^2	0.545		Adj. R^2	0.398		Adj. R^2	0.629		Adj. R^2	0.260	
χ^2_{SC}	.31084[.577]		χ^2_{SC}	1.9501[.163]		χ^2_{SC}	.42676[.514]		χ^2_{SC}	.40259[.526]	
χ^2_{FF}	5.5449[.019]		χ^2_{FF}	12.455[.000]		χ^2_{FF}	5.2122[.022]		χ^2_{FF}	15.891[.000]	
χ^2_N	.49560[.781]		χ^2_N	13.563[.001]		χ^2_N	2.2359[.327]		χ^2_N	28.056[.000]	
χ^2_{HE}	10.057[.002]		χ^2_{HE}	29.915[.000]		χ^2_{HE}	6.3260[.012]		χ^2_{HE}	23.080[.000]	
F_{PSS}	6.871		F_{PSS}	4.481		F_{PSS}	7.357		F_{PSS}	5.381	
W_{LR}	4.7036[.030]		W_{LR}	10.6000[.001]		W_{LR}	73.3000[.000]		W_{LR}	.2877[.592]	
W_{SR}	1.3536[.245]		W_{SR}	10.2850[.001]		W_{SR}	11.1380[.001]		W_{SR}	19.0300[.000]	

*L_{q^+} and L_{q^-} stand for the long-run asymmetric coefficients on positive and negative cumulative order flows, which are obtained by $\lambda^+ = -\theta^+/\psi$ and $\lambda^- = -\theta^-/\psi$, respectively. F_{PSS} is the F–statistic testing for an asymmetric cointegration, and the associated critical values (for the case with unrestricted intercept and no trend, 2 I(1) regressors) are 4.14, 4.48 and 6.36 at 10%, 5%, and 1% significance levels. W_{LR} and W_{SR} stand for the Wald statistics testing the null hypotheses of the long–run symmetry and the weak short–run symmetry, both of which follow χ^2 distribution under the respective null. See also footnotes to Table 7.

(b) FRF, BEF, ITL, NLG

Table 9: Estimation Results of the Dynamic Asymmetric Model

DEM			GBP			JPY			CHF		
Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio
p_t	0.00	.18[.856]	p_t	-0.06	-1.88[.063]	p_t	-0.06	-1.21[.228]	p_t	-0.09	-2.86[.006]
q_t	0.13	1.10[.272]	q_t	-0.10	-1.24[.217]	q_t	0.05	.77[.439]	q_t	0.69	4.10[.000]
L_q	-27.80	-.16[.873]	L_q	-1.70	-1.41[.161]	L_q	0.96	.88[.381]	L_q	8.10	4.66[.000]
Δp_{t-2}	-24.76	-2.10[.039]	Δp_{t-1}	-23.20	-2.06[.042]	Δq_t	2.92	7.44[.000]	Δp_{t-1}	-17.31	-2.26[.027]
Δq_t	2.30	12.59[.000]	Δq_t	3.44	5.24[.000]	Δq_{t-5}	0.70	1.76[.082]	Δp_{t-10}	21.58	1.97[.053]
Δq_{t-2}	0.66	2.01[.048]	Δq_{t-1}	1.20	1.61[.111]	Δq_{t-11}	-0.64	-1.61[.111]	Δp_{t-12}	14.48	1.89[.063]
									Δq_t	6.79	11.22[.000]
									Δq_{t-8}	-1.22	-2.31[.024]
									Δq_{t-10}	-1.97	-2.39[.020]
Const.	-0.002	-.19[.843]	Const.	-0.03	-1.96[.054]	Const.	0.28	1.21[.230]	Const.	0.03	3.29[.002]
Adj. R^2	0.693		Adj. R^2	0.327		Adj. R^2	0.465		Adj. R^2	0.671	
χ^2_{SC}	.04999[.823]		χ^2_{SC}	1.7315[.188]		χ^2_{SC}	.01720[.896]		χ^2_{SC}	.01279[.910]	
χ^2_{FF}	1.6536[.198]		χ^2_{FF}	.70431[.401]		χ^2_{FF}	2.1508[.142]		χ^2_{FF}	9.7991[.002]	
χ^2_{N}	.82083[.663]		χ^2_{N}	68.871[.000]		χ^2_{N}	8.8398[.012]		χ^2_{N}	.01620[.992]	
χ^2_{HE}	5.2185[.022]		χ^2_{HE}	.91022[.340]		χ^2_{HE}	.57848[.447]		χ^2_{HE}	15.820[.000]	
F_{PSS}	2.137		F_{PSS}	1.837		F_{PSS}	0.762		F_{PSS}	8.621	

(a) DEM, GBP, JPY, CHF

continued overleaf...

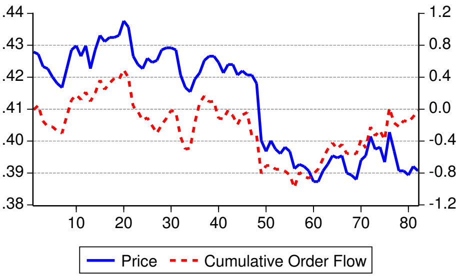
...*continued from previous page*

FRF			BEF			ITL			NLG		
Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio	Reg.	Coeff.	t-ratio
p_t	-0.23	-3.13[.002]	p_t	-0.16	-3.13[.003]	p_t	-0.003	-.10[.918]	p_t	-0.29	-3.57[.001]
q_t	1.91	2.49[.015]	q_t	-3.88	-2.95[.004]	q_t	0.37	.46[.644]	q_t	6.52	3.29[.002]
L_q	8.22	7.40[.000]	L_q	-24.40	-5.39[.000]	L_q	95.05	.08[.931]	L_q	22.49	9.61[.000]
Δq_t	9.85	8.03[.000]	Δp_{t-8}	20.39	1.77[.081]	Δp_{t-1}	-32.89	-3.22[.002]	Δq_t	17.07	2.63[.010]
Δq_{t-6}	2.07	2.11[.038]	Δp_{t-11}	21.62	1.91[.061]	Δp_{t-2}	-12.24	-1.23[.221]	Δq_{t-5}	15.07	2.35[.021]
			Δq_{t-6}	13.88	2.52[.014]	Δp_{t-4}	-13.95	-1.44[.153]			
			Δq_{t-8}	12.56	2.14[.036]	Δp_{t-5}	-18.97	-1.83[.071]			
			Δq_{t-14}	-17.31	-2.76[.008]	Δp_{t-6}	-20.68	-2.12[.037]			
						Δq_t	10.81	6.67[.000]			
						Δq_{t-8}	-2.09	-1.26[.209]			
Const.	0.38	3.14[.002]	Const.	0.55	3.13[.003]	Const.	0.03	.09[.922]	Const.	0.16	3.58[.001]
Adj. R^2	0.498		Adj. R^2	0.232		Adj. R^2	0.475		Adj. R^2	0.230	
χ^2_{SC}	.20318[.652]		χ^2_{SC}	3.2290[.072]		χ^2_{SC}	.05204[.820]		χ^2_{SC}	1.1835[.277]	
χ^2_{FF}	10.718[.001]		χ^2_{FF}	10.262[.001]		χ^2_{FF}	.11653[.733]		χ^2_{FF}	1.5814[.209]	
χ^2_{N}	1.6935[.429]		χ^2_{N}	47.554[.000]		χ^2_{N}	3.2066[.201]		χ^2_{N}	57.085[.000]	
χ^2_{HE}	11.811[.001]		χ^2_{HE}	10.360[.001]		χ^2_{HE}	5.8769[.015]		χ^2_{HE}	14.819[.000]	
F_{PSS}	6.387		F_{PSS}	5.086		F_{PSS}	0.389		F_{PSS}	6.424	

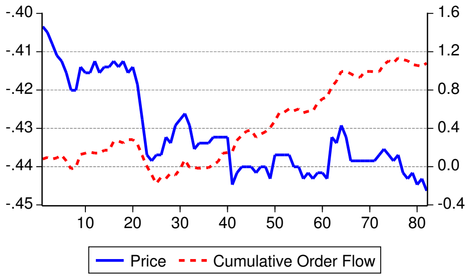
*L_q stands for the long-run coefficient on cumulative order flows, which is obtained by $\lambda = -\theta/\psi$. F_{PSS} is the F–statistic testing for a linear cointegration, and the associated critical values (for the case with unrestricted intercept and no trend, 1 I(1) regressor) are 4.78, 5.73 and 7.84 at 10%, 5%, and 1% significance levels. See also footnotes to Table 7.

(b) FRF, BEF, ITL, NLG

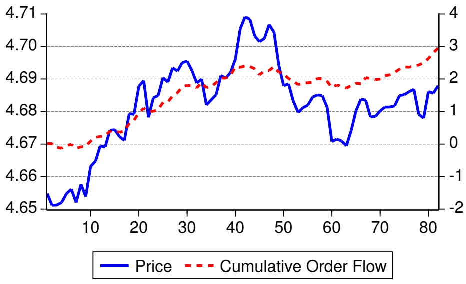
Table 10: Estimation Results of the Dynamic (Symmetric) Linear Model



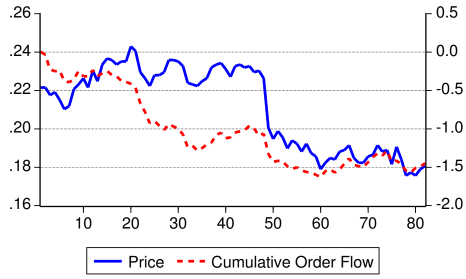
(a) DEM market



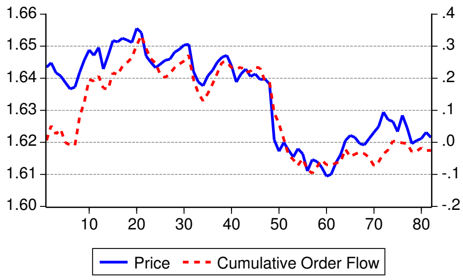
(b) GBP market



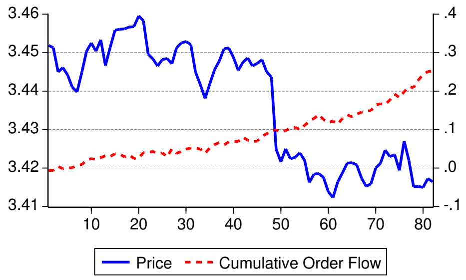
(c) JPY market



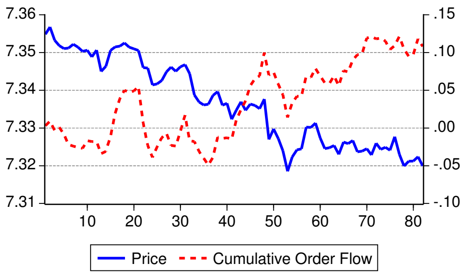
(d) CHF market



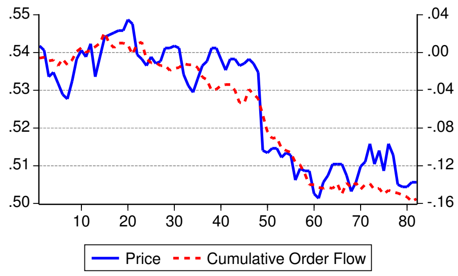
(e) FRF market



(f) BEF market

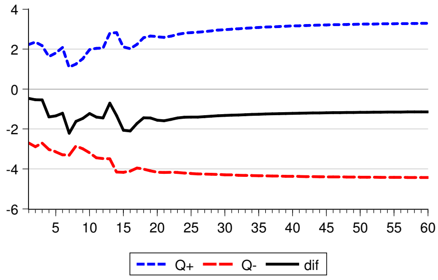


(g) ITL market

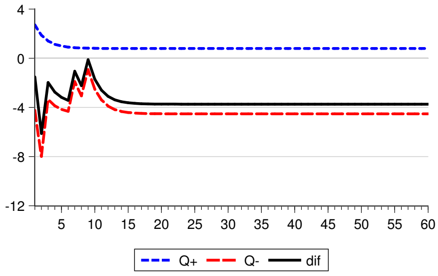


(h) NLG market

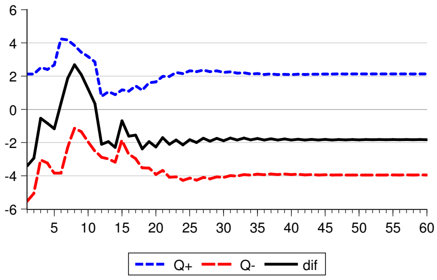
Figure 3: Bilateral Exchange Rates and Cumulative Order Flows



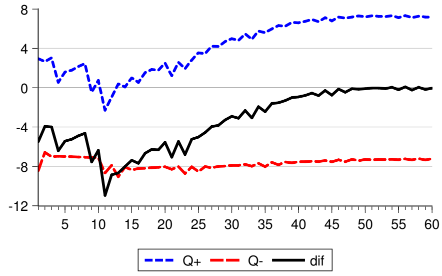
(a) DEM market



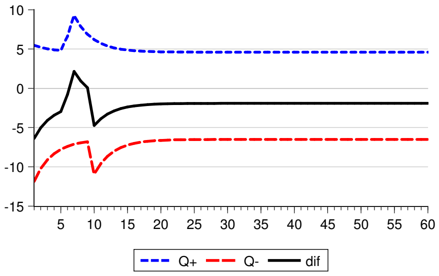
(b) GBP market



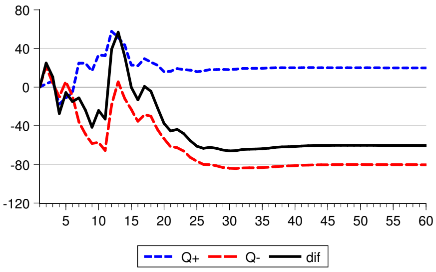
(c) JPY market



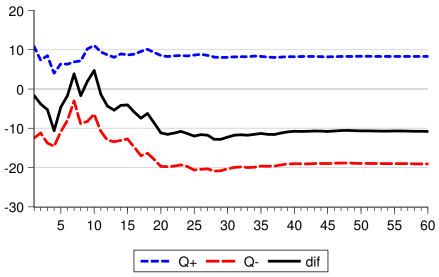
(d) CHF market



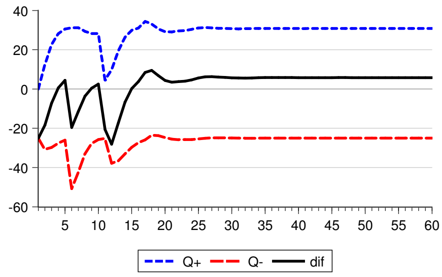
(e) FRF market



(f) BEF market

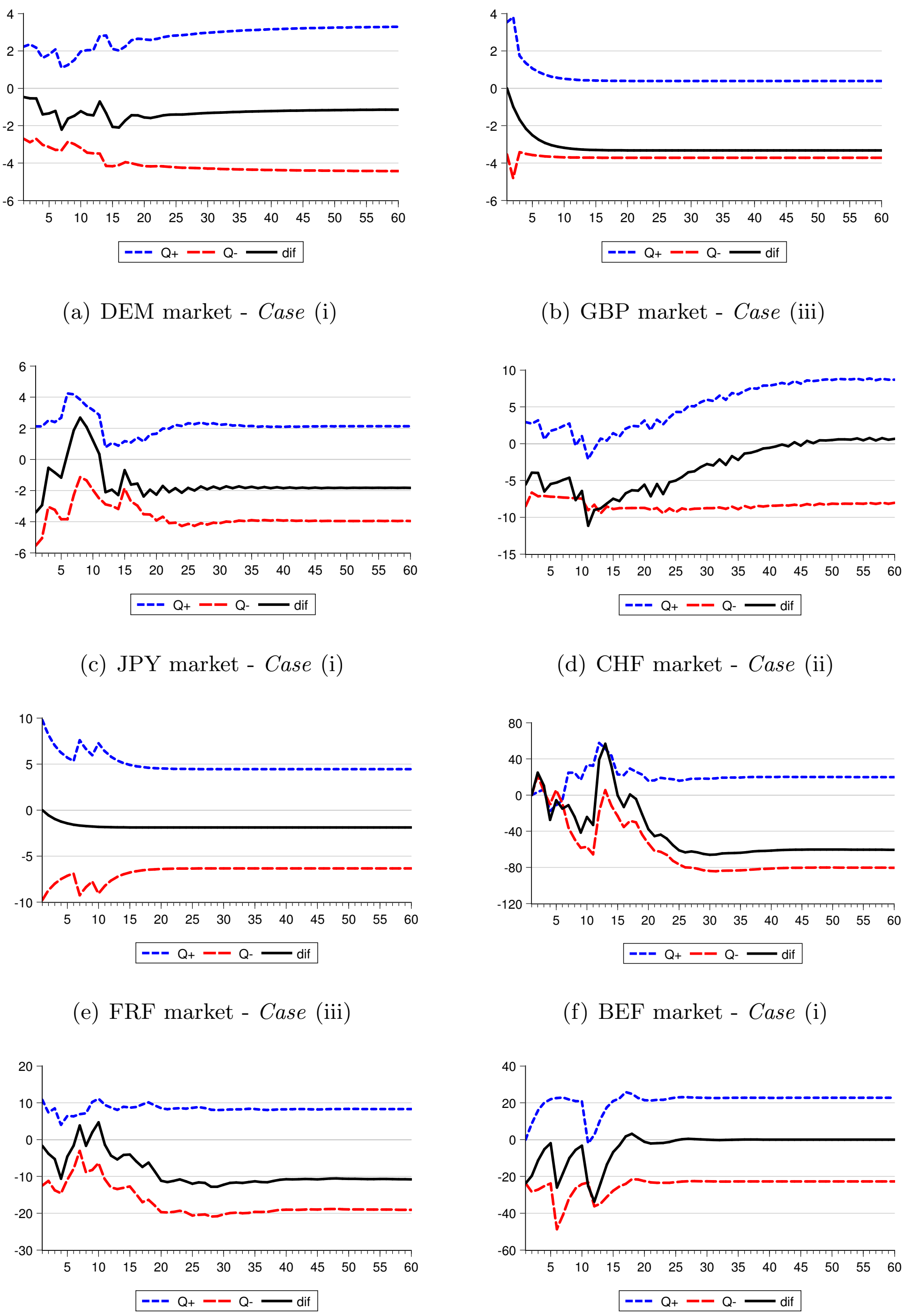


(g) ITL market



(h) NLG market

Figure 4: Dynamic Multiplier Effects - Asymmetric LR & SR (*Case* (i))



(a) DEM market - *Case* (i)

(b) GBP market - *Case* (iii)

(c) JPY market - *Case* (i)

(d) CHF market - *Case* (ii)

(e) FRF market - *Case* (iii)

(f) BEF market - *Case* (i)

(g) ITL market - *Case* (i)

(h) NLG market - *Case* (ii)

Figure 5: Dynamic Multiplier Effects - Statistically Selected Cases