Asymmetric Price Impacts of Order Flow on Exchange Rate Dynamics*

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October 5, 2011

Abstract

We generalize the portfolio shifts model of exchange rate determination advanced by Evans and Lyons (2002a; b). Our model allows for asymmetric price impacts of order flow, and for persistent mispricing. Using the Reuters D2000-1 dataset, we find strong evidence of an asymmetric cointegrating relationship between the exchange rate and order flow. Specifically, the price impact of dollar-selling pressure is overwhelmingly stronger than that of dollar-buying pressure, i.e. traders respond asymmetrically to selling and buying pressures of the dollar. Our results also reveal the complex price discovery process, and different feedback trading strategies in foreign exchange markets.

JEL Classifications: C22, F31, G15.

Keywords: Exchange Rate, Order Flow, Asymmetric Price Impacts, Underreaction, Overreaction.

* 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, Guay Lim, 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.

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1 Introduction

The poor performance of the macroeconomic (macro) approach to exchange rate determination is well documented (e.g. Meese and Rogoff, 1983; Frankel and Rose, 1995; Flood and Taylor, 1996). Meese and Rogoff (1983) suggest that one possible cause is the omission of a key variable in macro exchange rate models. That omitted variable could carry publicly unavailable, but relevant information for the determination of exchange rates. However, such a variable does not feature in the macro framework since the macro approach assumes that all the relevant information for exchange rate determination is publicly available and directly integrated in exchange rates.

By contrast, the microstructure (micro) approach recognizes the existence of nonpublic information and emphasizes the central role of the trading process. In particular, this approach assumes that nonpublic information is dispersed among the public and is integrated into exchange rates through the nontransparent trading process (e.g. Lyons, 2001; Evans, 2002; Evans and Lyons, 2002a; 2002b; 2005; 2008; Love and Payne, 2008; Rime, Sarno, and Sojii, 2010). Order flow, a product of the trading process, is the proxy for the information flow. Defined as the difference between selling and buying orders with seller-initiated (buyer-initiated) trades taking a negative (positive) sign, a negative (positive) order flow signals selling (buying) pressure and predicts a negative (positive) return. Hence, existing micro studies often focus on the relation between exchange rate and order flow and is more successful in explaining exchange rate movements than existing macro studies (e.g. Evans and Lyons, 2002a; b).

However, existing micro studies predominantly rely on the static regression of exchange rate return on order flow in empirical analysis. In this respect, existing micro studies are limited in uncovering possible mispricing and the dynamic price discovery process in foreign exchange (FX) markets. Two possible explanations for the reliance on the static return regression are: (i) theoretical micro models are built on the simple assumption of continuous market equilibrium (Evans and Lyons, 2002a; b), hence no adjustment is required; and (ii) empirical studies fail to provide conclusive evidence of a cointegrating relationship between the exchange rate and order flow (e.g. Bjønnes and Rime, 2005; Boyer and van Norden, 2006; and Berger, Chaboud, Cherenko, Howorka, and Wright, 2008), which hinders the use of dynamic error-correction models. The assumption of continuous market equilibrium holds only if all agents are fully rational, which is not always plausible in practice. Meanwhile, the inconclusive evidence on cointegration could be due to neglecting an important fact that the exchange rate responds asymmetrically to favorable and unfavorable information. For example, Andersen, Bollerslev, Diebold, and Vega (2003) analyze the impacts of macro announcements on exchange rates, and find that bad news has greater impact than good news does.

We aim to develop a general micro model of exchange rate determination by significantly extending the portfolio shifts framework of Evans and Lyons (2002a; b), the cornerstone of micro exchange rate models. First, we decompose order flow into positive and negative components to represent buying and selling pressures. We then allow for the asymmetric responses of traders to buying and selling pressures. In our model, these asymmetric responses of traders stem from their asymmetric risk aversion degrees to favorable and unfavorable trading information. Second, we assume that mispricing (overreaction or underreaction) can happen and persist in the short run due to the biased behaviors of noise traders and the limited arbitrage of rational traders.

Our extensions to the original framework of Evans and Lyons (2002a; b) rely on two strands of studies. First, a growing number of studies demonstrate the asymmetric responses of individuals to positive and negative information. Studies in psychology find that unfavorable information has a stronger impact on impressions than favorable information does (e.g. 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 behavior than positive information does. Moreover, the prospect theory advanced by Kahneman and Tversky (1979)
suggests that individuals react asymmetrically to a loss and a gain in value of the same magnitude with the former inducing a stronger reaction. Hence, if FX traders do respond asymmetrically to favorable and unfavorable trading information, the imposition of a linear relationship between the exchange rate and order flow is clearly misleading. In their path-breaking study, Evans and Lyons (1999) note that the linearity of their portfolio shifts specification depends crucially on several simplifying assumptions, some of which are rather strong on empirical grounds.

Second, a number of studies in behavioral finance demonstrates that in the short run the biased behaviors of ‘pseudo-informed’ noise traders often cause market underreaction or over-reaction while various risks in financial markets often limit the arbitrage of rational traders. Daniel, Hirshleifer, and Subrahmanyam (1998) attribute underreaction and overreaction to psychological biases of investors (overconfidence and biased self-attribution). Barberis, Shleifer, and Vishny (1998) relate underreaction and overreaction to investor sentiment (failures of individual judgment under uncertainty), specifically investors pay more attention to the strength than to the statistical weight of the information. Meanwhile, rational traders who are risk-averse, short-lived, and face with various risks or agency problems, often fail to eliminate mispricing immediately and completely. In particular, DeLong, Shleifer, Summers, and Waldmann (1990a) suggest that the risk incurred from unpredictable beliefs of noise traders prevents rational arbitrageurs from betting aggressively against noise traders. 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. Because of the limited arbitrage, mispricing persists, rendering markets not always in equilibrium.

The distinctive features of our model, called the Dynamic Asymmetric Portfolio Shifts (DAPS) model, from existing micro exchange rate models lie in its allowance for the asymmetric price impacts of buying and selling pressures in both the short run and the long run, and for the persistent mispricing. Our model nests the symmetry in the price impacts of buying and selling pressures, and the continuous market equilibrium as two special cases. If the symmetry holds only, our model becomes a dynamic symmetric portfolio shifts model. If the continuous market equilibrium holds only, our model becomes a static asymmetric portfolio shifts model. If both of these two cases hold jointly, our model regresses to the (static symmetric) portfolio shifts model of Evans and Lyons (2002b). The validity of our theoretical model can be analyzed flexibly by employing the Nonlinear Auto-Regressive Distributed Lag (NARDL) model of Shin, Yu and Greenwood-Nimmo (2009).

Moreover, our model accommodates both the short-run and the long-run price impacts of order flow, thus it provides a natural framework to assess market underreaction and overreaction. By construction of our model, the long-run price impacts of buying and selling pressures represent the asymmetric cointegrating (equilibrium) relationship between the exchange rate and (cumulative) order flow. Thus, underreaction and overreaction are measured in terms of the short-run exchange rate movement relative to this cointegrating relationship. Specifically, if the short-run upward movement of the exchange rate under buying pressure is below (above) the equilibrium relationship between the exchange rate and positive order flow, the market underreacts (overreacts). Reversely, if the short-run downward movement of the exchange rate under selling pressure is above (below) the equilibrium relationship between the exchange rate and negative order flow, the market underreacts (overreacts). Then, through the use of dynamic multipliers, we can easily address the complex price discovery process in FX markets. This ability renders our model considerably superior to existing micro exchange rate models.

We use the Reuters Dealing 2000-1 interdealer trading dataset in eight currency spot markets (German mark, British pound, Japanese yen, Swiss franc, French franc, Belgian franc, Italian lira, and Netherlands guilder, all against the US dollar) over a four-month period from 1 May

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to 31 August 1996. Our cointegration test results provide strong evidence of an asymmetric cointegrating relationship between the exchange rate and (cumulative) order flow in all eight markets. Specifically, the price impact of dollar-selling pressure is overwhelmingly stronger than that of dollar-buying pressure in both the short run and the long run. This finding indicates that traders react more strongly to the unfavorable trading information for the dollar than they do to the favorable one. Our empirical results further show that short-run exchange rate movements deviate considerably from the cointegrating relationship between the exchange rate and order flow. These deviations demonstrate that the equilibrium exchange rate level is not reached instantly at the end of each trading day due to the biased behaviors of noise traders and the limited arbitrage of rational traders, as argued by DeLong, Shleifer, Summers, and Waldmann (1990a; b), Shleifer and Vishny (1997), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Abreu and Brunnermeier (2002; 2003).

Next, we find two typical patterns of the price discovery process among eight markets: one following market overreactions and the other following underreactions. The former displays overshooting and volatile adjustments in the short run. Our theoretical model suggests that the excess speculative demand (excess liquidity) following market overreactions triggers such a volatile episode of short-run exchange rate movement. However, this liquid market condition in conjunction with the nature of mispricing, i.e. overreaction, are likely to offer arbitrageurs a greater incentive (than in an illiquid market condition) to join the correction process without delay. Hence, we observe that exchange rates return to their equilibrium levels relatively quickly after overreactions. On the contrary, the price discovery process following market underreactions exhibits a gradual and persistent adjustment pattern, which can be explained by the low speculative demand (low liquidity) following underreactions. In addition, we observe that the larger is the mispricing (as measured by the differential between the short-run and the long-run price impacts of order flow), the faster is the overall adjustment speed. This finding is consistent with those of Abreu and Brunnermeier (2002), and Cai, Faff and Shin (2011).

Finally, our empirical results provide evidence on feedback trading strategies in FX markets. In particular, positive feedback trading dominates in underreacting markets, which reflects the gradual but dominant arbitraging activity of rational traders. Working as a stabilizing force, this feedback trading strategy pushes the markets gradually towards equilibrium. By contrast, in overreacting markets the trend-chasing (positive feedback) trading strategy of noise traders (e.g. DeLong, Shleifer, Summers, and Waldmann, 1990b; Hong and Stein, 1990) often causes delayed overshooting and overadjusting in the short run. However, overreactions are corrected by negative feedback trading at longer horizons, which reflects the behavior of arbitrageurs. These findings provide support for two regularities in financial markets observed in terms of return autocorrelations: positive short-run autocorrelations (momentum) signal underreactions while negative long-run autocorrelations (reversal) signal overreactions, as analyzed in Barberis, Shleifer, and Vishny (1998), and Daniel, Hirshleifer, and Subrahmanyam (1998).

The rest of the paper is organized as follows. In Section 2 we briefly summarize the portfolio shifts model of Evans and Lyons (2002a; b). In Section 3 we develop our DAPS model. Section 4 describes the data and methodology, and presents our main empirical findings. Section 5 provides concluding remarks.

2 Portfolio shifts framework

Evans and Lyons (2002a; b) develop an intuitive Portfolio Shifts (PS) model to demonstrate that order flow conveys information about the market-clearing discount rate, and hence determines exchange rates (prices). Specifically, at the start of each trading day the realized, but unobservable customer-dealer orders reflect the uncertain public demands for foreign exchange.

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3Bacchetta and van Wincoop (2006) also provide a framework under which order flow precedes price.
Through the trading process, these demand realizations affect prices because price concessions are required for the rest of the market to reabsorb them.

The PS model follows a Bayesian-Nash Equilibrium (BNE) approach and relies on several key assumptions. First, the pure exchange economy consists of \( T + 1 \) trading periods (days) and two assets, one riskless (gross return equal to one) and the other risky. The payoff on the risky asset, \( R_t \), is composed of a series of increments, \( R_t = \sum_{j=0}^{t} \Delta R_j \) where \( \Delta R_t \sim iidN(0, \sigma^2_R) \) is the publicly observed increment before each period. Second, the dealership-type foreign exchange market comprises of \( N \) dealers and the public (nondealer customers) that is larger relative to the dealers. Third, all agents have an identical negative exponential utility function, denoted \( U_t = E_t[-\exp(-\theta W_{t+1})] \), where \( E_t \) is the expectations operator, \( W_{t+1} \) is the nominal wealth at the end of period \( t + 1 \), and \( \theta \) is the common constant absolute risk aversion (CARA) parameter.

Fourth, the aggregate demand of the public for the risky asset is not perfectly elastic. Notably, the second and third assumptions imply that the risk-bearing capacity of the public is much greater than that of the dealers, so the dealers have a comparative disadvantage in holding overnight positions. Thus, dealers attempt to end trading each day with no net position.

2.1 Trading process

All the transactions in each trading period are grouped into three trading rounds in chronological order. In round 1, dealers trade with the public. At the beginning of this round, all market participants observe the payoff increment, \( \Delta R_t \), that represents public information. Then, all dealers simultaneously and independently quote a common scalar price, \( P_1^t \) (round 1, period \( t \)), to customers. At this price, the dealers agree to buy and sell any amount. After trading with customers, each dealer receives a customer order realization, \( C_{1it} \sim N(0, \sigma^2_C) \) with \( C_{1it} < 0 \) indicating customers’ net selling (dealer \( i \)’s net buying). The aggregate customer-dealer order flow at the end of round 1 can be expressed as

\[
C_{1t} = \sum_{i=1}^{N} C_{1it}. \tag{2.1}
\]

\( C_{1it} \) is observable only to dealer \( i \) and represents the portfolio shifts of dealer \( i \)’s customers. \( C_{1t} \) is unobservable to all agents and represents the aggregate portfolio shifts of the public.

In round 2, dealers trade among themselves. All dealers simultaneously and independently quote a common price, \( P_2^t \), and trades with each other. At the close of this round, each dealer receives a net interdealer trade, \( \Delta Q_{it} \) with \( \Delta Q_{it} < 0 \) representing dealer \( i \)’s net selling, and all market participants observe the aggregate interdealer order flow, defined as

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

In round 3, dealers trade again with the public to share overnight risk while the trading motive of the public in this round is purely speculative. Conditional on available information from round 2, all dealers simultaneously and independently quote a common price, \( P_3^t \), to customers. Since the public has a finite risk-bearing capacity, the dealers set \( P_3^t \) so that the public is willing to absorb the inventory imbalances of the dealers (Evans and Lyons, 2002a; b). All dealers end the trading period with no net position, i.e.

\[
C_{1t} + C_{3t} = 0, \tag{2.3}
\]

where \( C_{3t} = \sum_{i=1}^{N} C_{3it} \) is the unobservable aggregate demand of the public in round 3, and \( C_{3it} \) is the customer order realization received by and observable only to dealer \( i \). Therefore, \( P_3^t \) reflects information about both \( \Delta R_t \) and \( \Delta Q_t \).

\(^4\)For simplicity, we follow Evans and Lyons (2002a; b) and consider the price instead of bid-offer spread.
2.2 Static symmetric portfolio shifts model

The PS model is derived from several key propositions (see Evans and Lyons, 1999; 2002a; b). First, to be consistent with BNE and to avoid an arbitrage condition, all dealers quote a common price in each trading round. Second, the interdealer trade in round 2, \( Q_{it} \), is proportional to the customer-dealer trade in round 1:

\[
\Delta Q_{it} = \alpha C_{1t}, \quad \forall i = 1, \ldots, N, \quad (2.4)
\]

where \( \alpha \) is a positive constant and captures the trading profile of the dealers. Thus, the observed \( \Delta Q_{it} \) in round 2 reflects the unobservable \( C_{1t} \) in round 1. Third, the aggregate public demand in round 3 is a linear function of the expected returns, specifically

\[
C_{3t}^3 = \gamma \left[ E_t \left( P_{t+1}^3 | \Omega_{t}^3 \right) - P_t^3 \right], \quad (2.5)
\]

where \( \Omega_{t}^3 \) is the available information set in round 3, and \( \gamma = (\theta \sigma_{R|^t_{\Omega}})^{-1} \) represents the positive price sensitivity of demand and captures the aggregate risk-bearing capacity of the public, \( \theta \) is the CARA parameter, and \( \sigma_{R|^t_{\Omega}} \) is the conditional variance of return.

From (2.1) to (2.4), the link between order flows of three trading rounds is derived as

\[
C_{1t} = -\frac{\Delta Q_{1t}}{\alpha} = -C_{3t}^3. \quad (2.6)
\]

Thus, the price in round 3 can be written as

\[
P_t^3 = E_t \left[ P_{t+1}^3 | \Omega_{t}^3 \right] - \frac{C_{t}^3}{\gamma} = E_t \left[ P_{t+1}^3 | \Omega_{t}^3 \right] + \frac{\Delta Q_{1t}}{\alpha \gamma} = E_t \left[ P_{t+1}^3 | \Omega_{t}^3 \right] + \lambda \Delta Q_{t}, \quad (2.7)
\]

where \( \lambda = (\alpha \gamma)^{-1} > 0 \) captures the price impact of order flow and depends on the aggregate risk-bearing capacity of the public, \( \gamma \), and on the trading profile of the dealers, \( \alpha \). The right-hand side of (2.7) represents the cumulative expected payoffs on the risky asset up to period \( t \), \( E_t \left[ P_{t+1}^3 | \Omega_{t}^3 \right] \), that is adjusted for the risk premium in period \( t \), \( \lambda \Delta Q_{t} \) (Evans and Lyons, 1999). Thus, (2.7) can be rewritten in terms of cumulative payoffs adjusted for risk premia as

\[
P_t^3 = \sum_{j=0}^{t} (\Delta R_j + \lambda \Delta Q_j) = R_t + \lambda Q_t, \quad (2.8)
\]

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 \( \Delta P_t^3 = P_t^3, \quad (2.8) \) can be expressed as

\[
\sum_{j=0}^{t} \Delta P_j^3 = \sum_{j=0}^{t} (\Delta R_j + \lambda \Delta Q_j). \quad (2.9)
\]

Under BNE and the assumption that the public holds rational expectations, the price change from round 3 of period \( t - 1 \) to round 3 of period \( t \) is simplified as

\[
\Delta P_t = \Delta R_t + \lambda \Delta Q_t. \quad (2.10)
\]

(2.10) is the PS model that explains how the public and nonpublic information is channeled into the price: (i) the direct impact of public information via \( \Delta R_t \) (directly integrated in price); (ii) the indirect impacts of public information via induced order flow, \( \Delta Q_t \); and (iii) the direct impact of nonpublic information via order flow \( \Delta Q_t \). The PS model crucially depends upon the market clearing condition (2.3). The price impact of order flow is also constrained to be constant over time and homogeneous under buying and selling pressures. In practice, the validity of these constraints is questionable, in particular when not all of the market participants are fully rational and/or when the risk preferences of the public are heterogeneous with respect to buying and selling pressures. Moreover, the static nature of the PS model is unable to provide any prediction for the dynamic price adjustment process whenever market disequilibrium occurs.
3 Dynamic asymmetric portfolio shifts model

We derive a general portfolio shifts model by relaxing two restrictive conditions of the PS model. Specifically, we account for market underreaction and overreaction, and allow for the asymmetric price impacts of buying and selling pressures.

3.1 Asymmetric responses to buying and selling pressures

There is growing evidence in psychology (Skowronski and Carlston, 1989; Vonk, 1996), politics (Bloom and Price, 1975; Lau, 1985), and economics (Bowman, Minehart, and Rabin, 1999; Andersen, Bollerslev, Diebold, and Vega, 2003; Soroka, 2006) suggesting that individuals respond asymmetrically to positive and negative information with the latter generating a stronger reaction. The prospect theory of Kahneman and Tversky (1979) offers a descriptive model of decision making under risk 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, Knetsch, and Thaler (1986) also stress that the response of individuals to unfavorable changes is more intense than it is to favorable changes.

Under the PS framework, selling pressure ($\Delta Q_t < 0$) realized in round 2 indicates that the risk-averse public on average sells the risky asset in favor of the riskless one. This selling pressure signals bad news or an unfavorable change, since it predicts a negative return (loss) for the risky asset in period $t$. Conversely, by predicting a positive return (gain) buying pressure ($\Delta Q_t > 0$) signals good news or a favorable 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:

$$\Delta Q_t = \Delta Q_t^+ + \Delta Q_t^-, \ t = 0, ..., T,$$

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

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5Sager and Taylor (2006) sketch several features of a more practical micro exchange rate model in which dealers do not always clear their positions overnight since the public does not absorb the daily imbalances of the dealers fully. Meanwhile, Andersen, Bollerslev, Diebold, and Vega (2003) show that the price impact of bad news is greater than that of good news.
Now consider the exchange between the dealers and the public in round 3 in up and down markets. Recall that in this round the dealers have to offer price concessions for the public to reabsorb their risky imbalances. In up markets, the dealers want the public to sell the risky asset when it is gaining in value. On the contrary, in down markets, the 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 which is acquired and which is given up. When the public agrees to exchange, they hold the riskless asset in the favorable market while they hold the risky one in the unfavorable 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 attribute of the public can be incorporated in the PS framework by allowing their risk aversion to be greater in down markets than in up markets as follows:

\textbf{Assumption 3.1} All agents have the following negative exponential utility function:

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

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 CARA parameters for all agents in down and up markets, respectively.

\( \theta^- > \theta^+ \) implies that the public responds more strongly to selling pressure and demands a greater price concession to absorb risk than they do 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:

\[ H_t = \sum_{i=1}^{s} \tau_i |C_{t-i}^3|, \quad 0 < \tau_i < \frac{1}{s}, \quad s < t, \quad (3.2) \]

where \( C_{t-1}^3, \ldots, C_{t-s}^3 \) are the public’s past aggregate consumptions of the risky asset in round 3 (purely speculative demand), and \( \tau_i \)'s are the sensitivity parameters with respect to past aggregate consumptions. 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 the restriction \( 0 < \tau_i < s^{-1} \).

Notice that by construction \( H_t > 0 \) because \( H_t = 0 \) only if \( C_{t-1}^3 = C_{t-2}^3 = \ldots = C_{t-s}^3 = 0 \), meaning that the market does not function for \( s \) periods. Hence, the risky-asset consumption ratio, \( c_t / H_t > 0 \) when \( c_t > 0 \), and vice versa. More importantly, \( C_{t-i}^3, \ i = 1, \ldots, s, \) reflects the amount of the risky asset changing hands at the closing price or the risk-bearing capacity of the public at the end of period \( t - i \). 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 the dealers’ attempts to clear their inventory imbalances in round 3 of each trading period relies crucially on the time-varying liquidity provision.\footnote{Abel (1999) measures the utility of agents by the consumption ratio and shows that the absolute risk aversion of all agents with respect to consumption, defined as \( \theta_t = - \left( \frac{U''(c_t)}{U'(c_t)} \right) = \left( \frac{c_t}{\pi_t} \right) \), is time-varying due to the time-varying habit level \( H_t \).}
3.2 Market underreaction and overreaction

Existing studies in behavioral finance provide both theoretical frameworks and pervasive empirical evidence of overreactions and underreactions in stock and foreign exchange markets. In particular, Barberis, Shleifer, and Vishny (1998) provide statistical evidence that investors tend to underreact to good news, but overreact to a series of good or bad news. These underreacting and overreacting behaviors are mainly attributed to investor psychology or sentiment. To provide a more general PS framework with the possibility of market overreactions and underreactions, we introduce the presence of heterogeneous traders by the following assumption:

**Assumption 3.2** The operating foreign exchange market is dealership-type with \( N \) dealers and a continuum of nondealer customers that is large relative to the \( N \) dealers and consists of both rational and noise traders.

Our model relies on existing studies on the biased behaviors of noise traders and the limits of arbitrage. In particular, with the presence of noise traders whose sentiment is partly unpredictable, mispricing can occur and persist because short-lived, risk-averse rational traders, who face with fundamental risk, noise trader risk (DeLong, Shleifer, Summers, and Waldmann, 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 behaviors 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 returns without bearing any extra risk, and thus remove mispricing immediately.

Lyons (1997) notes that two distinctive features of the simultaneous trade model from the rational expectations models are: (i) dealers have to contend with inventory shocks, i.e. undesired open positions, that are frequent and nontrivial; and (ii) when submitting orders dealers cannot condition on the market-clearing price level that is unknow n and only revealed through the trading process. Suppose that the market underreacts (overreacts) in round 1 of period \( t-j \), \( j = 1, ..., r \leq s \), due to the biased behaviors of noise traders. Then, the aggregate customer-dealer trade in round 1, \( C_{t-j}^1 \), does not reflect the correct market condition in period \( t-j \), denoted by \( C_{t-j}^{1*} \), i.e. \( C_{t-j}^1 < C_{t-j}^{1*} \). This deviation is then passed on to the dealers in trading rounds 2 and 3 of period \( t-j \), and causes mispricing, i.e. \( P_{t-j}^3 < P_{t-j}^{3*} \) \( (P_{t-j}^3 > P_{t-j}^{3*}) \) with \( P_{t-j}^{3*} \) being the equilibrium price level conditional on the information set in period \( t-j \). Because of the limited arbitrage, this mispricing can persist beyond period \( t-j \).

By construction, the persistent market underreactions (overreactions) in periods \( t-1, ..., t-r \) can decrease (increase) the habit level in period \( t \), resulting in a relatively less (more) liquid market. Consequently, the dealers cannot unload their risky imbalances in a liquidity-constrained market, and end up holding net positions overnight. Alternatively, in an excessively liquid market, the dealers not only clear their initial imbalances but also take on new imbalances in the opposite direction.

To accommodate the possibility of market disequilibrium, we relax the market clearing condition of the PS model as follows:

\[ C_t^1 + C_t^3 = \delta_t, \]

where \( \delta_t \) is the unobservable aggregate imbalance of the market given by

\[ \delta_t = \sum_{i=1}^{N} \delta_{it}, \quad \delta_{it} \sim (0, \sigma^2_{\delta}), \quad \sigma^2_{\delta} \neq 0, \]

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7Chordia, Roll, and Subrahmanyam (2002) show that aggregate order imbalances in the stock market reduce market liquidity and cause market-maker’s inventories to experience periodic strains. Such inventory strains could persist beyond a trading day, leaving extended effects on liquidity.
and $\delta_t$ 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 the dealers at the end of period $t$. Under $\Delta \omega > 0$ and $\Delta \epsilon < 0$, the market is not always in equilibrium at the end of each trading period though the market will return to equilibrium in the long run.

Depending on the value and sign of the dealers’ aggregate inventory imbalance, $I_t$, we project three likely outcomes at the end of each period in Table 1. Case 1 shows that the market is in equilibrium because the dealers can clear their inventory imbalances. Cases 2 and 3 describe the situations where underreactions and overreactions result in market disequilibrium in period $t$. In Case 2, the dealers’ 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 indicates that $P_t^3$ does not include the sufficient price concession (risk premium) accounting for the low liquidity condition caused by the underreacting behavior of noise traders. In Case 3, due to excess speculative demand (increasing habit level), the dealers not only clear their initial inventory imbalances from rounds 1 and 2, but also take on new inventory imbalances in the opposite sign with their quoted price in round 3, $P_t^3$. This reflects that $P_t^3$ offers a higher price concession than required under the excess liquidity condition triggered by the overreacting behavior of the noise traders.

<table>
<thead>
<tr>
<th>Case</th>
<th>R. 1 $C_t^1$</th>
<th>R. 2 $\Delta Q_t$</th>
<th>R. 3 $C_t^3$</th>
<th>$C_t^1$ vs. $C_t^3$</th>
<th>$I_t$ ($= -\delta_t$)</th>
<th>Speculative demand</th>
<th>Market condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(+)</td>
<td>(+)</td>
<td>(−)</td>
<td>$</td>
<td>C_t^{1+}</td>
<td>=</td>
<td>C_t^{3−}</td>
</tr>
<tr>
<td></td>
<td>(−)</td>
<td>(−)</td>
<td>(+)</td>
<td>$</td>
<td>C_t^{1−}</td>
<td>=</td>
<td>C_t^{3+}</td>
</tr>
<tr>
<td>2</td>
<td>(+)</td>
<td>(+)</td>
<td>(−)</td>
<td>$</td>
<td>C_t^{1+}</td>
<td>&gt;</td>
<td>C_t^{3−}</td>
</tr>
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<td></td>
<td>(−)</td>
<td>(−)</td>
<td>(+)</td>
<td>$</td>
<td>C_t^{1−}</td>
<td>&gt;</td>
<td>C_t^{3+}</td>
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<tr>
<td>3</td>
<td>(+)</td>
<td>(+)</td>
<td>(−)</td>
<td>$</td>
<td>C_t^{1+}</td>
<td>&lt;</td>
<td>C_t^{3−}</td>
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<tr>
<td></td>
<td>(−)</td>
<td>(−)</td>
<td>(+)</td>
<td>$</td>
<td>C_t^{1−}</td>
<td>&lt;</td>
<td>C_t^{3+}</td>
</tr>
</tbody>
</table>

Notice that in Case 2 the aggregate inventory imbalance of the dealers, $I_t$, and market order flows in rounds 1 and 2 (which indicate the market direction) are of the opposite signs, suggesting that the risk exposure of the dealers and the market direction are negatively correlated. By contrast, the risk exposure of the dealers is positively correlated with the market direction in Case 3. In sum, Cases 2 and 3 show that the dealers have to hold undesired imbalances overnight due to insufficient or excess speculative demand caused by the biased behaviors of the noise traders. We summarize the important implication of this discussion in the following assumption:

**Assumption 3.3** Let $\omega$ be the correlation coefficient between the interdealer order flow, $\Delta Q_t$, and the aggregate inventory imbalance of dealers, $I_t$, then $\omega < 0$ ($\omega > 0$) indicates market underreaction (overreaction), signaling that the market speculative demand is insufficient (excess).

The mainstream literature on market efficiency and noise trading (e.g., Figlewski, 1979; Kyle, 1985; Campbell and Kyle, 1988; DeLong, Shleifer, Summers, and Waldmann, 1990b) suggests that the adjustment process towards equilibrium consists of two competing forces: one by the informed rational traders and the other by the pseudo-informed noise traders. The former counters deviations of prices from fundamentals, hence this type of traders works as the stabilizing force. The latter destabilizes the market by buying when prices are high and selling when prices are low on average, thus this type of traders drives prices away from fundamentals. DeLong, Shleifer, Summers, and Waldmann (1990b) suggest that noise traders can 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. Therefore, we expect that the heterogeneous trading behaviors of rational and noise traders determine the dynamic price adjustment process towards equilibrium in underreacting and overreacting markets.

3.3 Dynamic asymmetric portfolio shifts model

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

\[
C_{t+} = \frac{\Delta Q_{t}^+}{\alpha} = -C_{t}^+ + \delta_{t}^U ,
\]

\[
C_{t-} = \frac{\Delta Q_{t}^-}{\alpha} = -C_{t}^+ + \delta_{t}^D,
\]

where \(\delta_{t}^U\) and \(\delta_{t}^D\) are the (accumulated) market imbalances in the up and the down markets such that \(\delta_{t} = \delta_{t}^U + \delta_{t}^D\). We define \(I_{t}^U(=-\delta_{t}^U)\) and \(I_{t}^D(=-\delta_{t}^D)\) as the dealers’ inventory imbalances in the up and the down markets. \(C_{t+}(C_{t-})\) represents the aggregate customer-dealer order in the up (down) market at the end of round 1 while \(C_{3+}(C_{3-})\) is the public’s aggregate demand for the risky asset at the end of round 3 in the up (down) market.

We modify (2.7) and express the price level at the end of round 3 in the up market as

\[
P_{3+} = E \left( P_{t+1}^3 | \Omega_t^3 \right) + \frac{\Delta Q_{t}^+}{\alpha \gamma^+} + \frac{\delta_{t}^U}{\gamma^+} = R_{t}^+ + \lambda^+ Q_{t}^+ - \frac{\delta_{t}^U}{\gamma^+} ,
\]

where \(P_{3+} = \sum_{j=0}^{t} \Delta P_{j+}^+, R_{t}^+ = \sum_{j=0}^{t} \Delta R_{j}^+, \) and \(Q_{t}^+ = \sum_{j=0}^{t} \Delta Q_{j}^+\). Here, \(\Delta P_{j+}^+\) and \(\Delta R_{j}^+\) are the price change and the pay-off increment associated with the up market (\(\Delta Q_{j}^+\)). \(\gamma^+ = (\theta^+ \sigma^2_R(\Omega_t)^{-1}\) and \(\lambda^+ = (\alpha \gamma^+)^{-1}\) capture the risk bearing capacity of the public in the up market and the price impact of buying pressure, respectively. Similarly, the price level at the end of round 3 in the down market can be written as

\[
P_{3-} = R_{t}^- + \lambda^- Q_{t}^- - \frac{\delta_{t}^D}{\gamma^-} ,
\]

where \(P_{3-} = \sum_{j=0}^{t} \Delta P_{j-}^-, R_{t}^- = \sum_{j=0}^{t} \Delta R_{j}^-, \) and \(Q_{t}^- = \sum_{j=0}^{t} \Delta Q_{j}^-\). \(\gamma^- = (\theta^- \sigma^2_R(\Omega_t)^{-1}\) and \(\lambda^- = (\alpha \gamma^-)^{-1}\).

Combining (3.7) and (3.8), we obtain the asymmetric level relationship between the price and (cumulative) order flow as follows:

\[
P_t = R_t + \lambda^+ Q_t^+ + \lambda^- Q_t^- + \xi_t,
\]

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

As discussed in Subsection 3.2 the inventory imbalances of the dealers can persist beyond a trading day. Thus, we make the following assumption:

\*\(\delta_{t}^U\) and \(\delta_{t}^D\) can be positive or negative, i.e. Cases 2 and 3 can occur in both the up and the down markets.
Assumption 3.4 \( \xi_t \) follows an AR(1) process:

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

where \( \rho \) captures the degree of persistence in the dealers’ inventory imbalance and \( u_t \) is the iid innovation with zero mean and constant variance \( \sigma_u^2 \).

For convenience, we rewrite Assumption 3.4 as

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

where \( \psi = (\rho - 1) \) measures 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 \( \xi_t = P^3_t - R_t - \lambda^+ Q^+_t - \lambda^- Q^-_t \) is the error correction term associated with the asymmetric level relationship (3.9).

There is a growing literature providing evidence of feedback trading behavior in both foreign exchange and other securities markets (Hasbrouck, 1991; Danielsson 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 expect to observe counteractive feedback trading strategies by the rational and the noise traders over several periods. To allow for feedback trading behaviors explicitly in our model, we assume:

Assumption 3.5 The feedback trading behaviors of agents can be captured by the following reduced form regression for the interdealer order flow, \( \Delta Q_t \):

\[
\Delta Q_t = \sum_{i=1}^{p} \phi_{Pi} \Delta P_{t-i} + \sum_{j=1}^{q} \phi_{Qi}^+ \Delta Q^+_{t-j} + \sum_{j=1}^{q} \phi_{Qi}^- \Delta Q^-_{t-j} + v_t, \tag{3.12}
\]

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

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

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

where \( \omega \) is the market reaction parameter that captures the contemporaneous association between the inventory imbalance of the dealers 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

\[
u_t = \omega \left( \Delta Q_t - \sum_{i=1}^{p} \phi_{Pi} \Delta P_{t-i} - \sum_{j=1}^{q} \phi_{Qi}^+ \Delta Q^+_{t-j} - \sum_{j=1}^{q} \phi_{Qi}^- \Delta Q^-_{t-j} \right) + e_t. \tag{3.14}
\]

\*Our feedback trading specification is similar to those in Hasbrouck (1991), and Cohen and Shin (2003). Contemporaneous feedback trading, considered by Danielsson and Love (2006), is ruled out in our framework because the dealers set \( P^3_t \) in round 3 of period \( t \) conditional on their aggregated information from round 2, \( \Delta Q_t \). Thus, \( \Delta P_t = P^3_t - P^3_{t-1} \) is clearly determined by \( \Delta Q_t \).
Then, substituting (3.14) in (3.11), we obtain the following error correction model, called the Dynamic Asymmetric Portfolio Shifts (DAPS) model:

\[
\Delta P_t = \psi \xi_{t-1} + \Delta R_t + \kappa^+ \Delta Q^+_{t-1} + \kappa^- \Delta Q^-_{t-1} + \sum_{i=1}^{p} \pi_i \Delta P_{t-i} + \sum_{j=1}^{q} \left( \varphi^+_j \Delta Q^+_{t-j} + \varphi^-_j \Delta Q^-_{t-j} \right) + \epsilon_t \tag{3.15}
\]

where \( \kappa^+ = \lambda^+ + \omega \), \( \kappa^- = \lambda^- + \omega \), \( \pi_i = -\omega \phi_{p_i} \), \( \varphi^+_j = -\omega \phi^+_{Q_j} \), and \( \varphi^-_j = -\omega \phi^-_{Q_j} \). In (3.15), \( \kappa^+ \) and \( \kappa^- \) represent the short-run contemporaneous price impacts of buying and selling pressures, respectively; \( \lambda^+ \) and \( \lambda^- \) represents the long-run equilibrium price impacts. \( \kappa^+ \) and \( \kappa^- \) are different from \( \lambda^+ \) and \( \lambda^- \) when \( \omega \neq 0 \), i.e. market disequilibrium occurs.

This model explicitly takes into account: (i) the asymmetric price impacts of buying and selling pressures in both the short run and the long run, (ii) the persistent inventory imbalance of the dealers (persistent mispricing), (iii) the correlation between the inventory imbalance of the dealers and the market direction, (iv) different feedback trading strategies. In general, under the DAPS framework, the biased behaviors of the noise traders cause short-run market disequilibrium while the different risk aversion degrees of the agents under buying and selling pressures result in the asymmetric pricing impacts of order flows. Clearly, when the market underreacts, i.e. \( \omega < 0 \), 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 the rational and the noise traders following underreactions and overreactions will determine the pattern and the direction of the dynamic price discovery process. In theory, market underreactions (\( \omega < 0 \)) are expected to be followed by positive feedback trading (i.e. \( \phi_{p_j}, \phi^+_{Q_j} \) and \( \phi^-_{Q_j} > 0 \) in (3.12)) while negative feedback trading (i.e. \( \phi_{p_j}, \phi^+_{Q_j} \) and \( \phi^-_{Q_j} < 0 \)) is expected to follow overreactions (\( \omega > 0 \)). Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) make similar predictions. These adjustment patterns following underreactions and overreactions likely reflect the behavior of the rational traders which stabilizes the market. However, with the presence of the noise traders in practice, any dynamic adjustment pattern can happen. For example, negative feedback trading could follow underreactions while positive feedback trading immediately after overreactions can cause the price to overshoot (DeLong, Shleifer, Summers, and Waldmann). These feedback trading behaviors clearly destabilize the market and move the price further away from its equilibrium. Generally, in the context of the DAPS model (3.15), we summarize that \( \pi_i, \varphi^+_j \) and \( \varphi^-_j > 0 \) signal the equilibrium-driven feedback trading strategy of the stabilizing force while \( \pi_i, \varphi^+_j \) and \( \varphi^-_j < 0 \) represents the feedback trading strategy of the destabilizing force, irrespective of whether the market is underreacting or overreacting. Hence, we can conclude that which of the two competing forces, the noise or the rational traders, prevails will determines the pattern and the speed of the dynamic price discovery process.

### 3.4 Dynamic price discovery process

We analyze how the market evolve dynamically towards equilibrium following underreactions and overreactions. Because noise traders are present and could follow or counter the trading strategy of rational traders, the speed and the pattern of the price discovery process crucially depend on the relative activeness of rational and noise traders, and on the trading strategy of noise traders. In the Appendix A we examine in details how the interaction between the rational and the noise traders defines the patterns of the price adjustment process. In what follows, we briefly discuss possible adjustment patterns in both underreacting and overreacting markets.

Suppose that market disequilibrium occurs in period \( t \) and the market returns to equilibrium after \( k \) (\( \leq T - t \)) periods, we then analyze possible events in each adjustment period \( t + i \), \( i = 1, 2, ..., k \). Next, connecting the possible events over \( k \) periods together provides us with the
alternative patterns of the price discovery process. Specifically, in underreacting markets all the possible outcomes in period \( t + i \) can be grouped into three following events: (A) gradual equilibrium adjustment, (B) fast but possible overshooting, and (C) counter-equilibrium adjustment. Meanwhile, in overreacting markets all the possible outcomes in period \( t + i \) can be grouped into three following events: (D) gradual equilibrium adjustment, (E) fast but possible overadjustment, and (F) overshooting adjustment.

Because the trading strategy of the rational traders is always equilibrium-driven while the trading strategy of the noise traders is either equilibrium-driven or counter-equilibrium, Events A and D likely signal the gradual arbitraging activity of the rational traders and the relative inactivity of the noise traders. By contrast, Events B, C, E and F reflect the activeness of the noise traders whose trading strategies could destabilize the market. Events B can be further decomposed into B1 (fast adjustment) and B2 (overshooting) while Event E can be further decomposed into E1 (fast adjustment) and E2 (overadjustment). Under the simplifying assumption that the market returns to equilibrium after 2 periods \( (k = 2) \), we connect the initial mispricing in period \( t \), possible price adjustments in period \( t + 1 \), and the equilibrium price in period \( t + 2 \) together, and present the alternative price adjustment patterns in Figure 2.

\[ \kappa^+ \] and \( \kappa^- \) represent the contemporaneous (short-run) price impacts of buying and selling pressures, respectively. \[ \lambda^+ \] and \( \lambda^- \) represent the equilibrium (long-run) price impacts of buying and selling pressures, respectively.

**Figure 2:** The price adjustment process towards equilibrium

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 overadjustment 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 delayed overshooting under Cases 2 and 3, respectively. The overshooting price movement is likely to be attributable to the trend-chasing behavior of the noise traders (e.g. Hong and Stein, 1990).

Abreu and Brunnermeier (2002) show that fundamentals work as an anchor around which the price fluctuates. Similarly, in our framework the long-run price impacts of order flow, \( \lambda^+ \) and \( \lambda^- \), are determined by fundamentals and form an upper and a lower bounds (anchors) (see Figure 2). When the price stays between these bounds, the market underreacts (Case 2), signaling that the speculative demand is relatively low. However, when the price is outside these bounds (above the upper and below the lower), the market overreacts (Case 3), reflecting excess speculative demand. Hence, mispricing within these bounds is expected to be more persistent than mispricing outside these bounds.

Next, we 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 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 negative feedback trading. In this regard, feedback trading strategy can be identified by assessing the correlation between the price movements (return correlation) over two consecutive periods. However, in our dynamic framework it is more plausible to determine feedback trading strategy with regards to the current mispricing condition. Specifically, in absolute terms, if the price is below its equilibrium level (underreacting market), positive feedback trading will push the price towards its equilibrium while negative feedback trading will pull it further away. On the other hand, when the price is above its equilibrium level (overreacting market), then negative feedback trading will bring it down towards its equilibrium, while positive feedback trading will shoot it further away.

Specifically, 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. Under Case 3, the negative feedback trading in period \( t + 1 \) will move the price towards its equilibrium (Events D or E1) or overadjust 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 underreactions (overreactions) generally drives the market towards equilibrium. Finally, Events B2 and E2 (overshooting/overadjustment) could occur in period \( t + 1 \) if the noise traders follow the trading strategy of the rational traders. 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 brings the price towards its equilibrium.

4 Empirical application

Empirical evidence shows that the direct impact of public information on exchange rates is relatively small (e.g. Hasbrouck, 1991; Evans, 2002; Evans and Lyons, 2002a; b; 2008). In particular, Evans and Lyons (2008) find that macro news can explain up to 30% of exchange rate variation but two thirds of its impact is indirect via order flow. Hence, we follow the Evans and Lyons (2002a) and assume that public information, \( \Delta R_t \), is immediately and directly integrated into exchange rates, and we do not examine the direct price impact of \( \Delta R_t \).
4.1 Data and methodology

We use the Reuters Dealing 2000-1 daily dataset that are analyzed in Evans and Lyons (2002a; b; 2008). The dataset contain direct interdealer transactions over a four-month period from 1 May to 31 August 1996 in eight currency spot markets, namely: German mark, British pound, Japanese yen, Swiss franc, French franc, Belgian franc, Italian lira and Netherland guilder, all against the US dollar. We henceforth refer to these currency markets as DEM, GBP, JPY, CHF, FRF, BEF, ITL and NLG, respectively. During the sample period, about 90% of the global direct interdealer transactions takes place through the Reuters Dealing 2000-1 system (Evans and Lyons, 2002a; b). The exchange rate on day $t$, $p_t$, is the natural logarithm of the last purchase-transaction price, $P_t$, 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, $\Delta q_t$, is measured as the difference between the numbers of buyer-initiated (positively signed) trades and seller-initiated (negatively signed) trades in thousands from 4PM on day $t-1$ to 4PM on day $t$. Hence, negative (positive) order flows signal net sales (purchases) of the dollar.

As a prelude to the cointegration analysis, 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 in Evans and Lyons (2002a) and Berger, Chaboud, Cherenko, Howorka, and Wright (2008).

Table 4 and Figure 3 around here

We provide the summary descriptive statistics for the order flow series in eight markets in Table 4. Columns 2, 3 and 4 report the numbers of days that end with positive, negative, and zero order flows, respectively. These numbers shows that all 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 and 10 show the total excess trades ($\sum |\Delta q_t|$) and the aggregate excess trades ($\sum \Delta q_t$), respectively. DEM has the highest total excess trades (the most heavily traded market), 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 exchange rates and cumulative order flows, and display that these two series move closely together in most markets. The noticeable exceptions are GBP and BEF in which the two series seem to diverge at the end of the sample period. Of the four heavily traded markets, i.e. DEM, GBP, JPY, and CHF, 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 yen exhibits a generally depreciating trend against the dollar while the mark and the Swiss franc display a clear appreciating trend. The pound seems to appreciate despite the mounting dollar-buying pressure. Furthermore, the exchange rates in DEM, CHF, FRF, BEF, and NLG exhibit a similar movement pattern.

The NARDL model advanced by Shin, Yu and Greenwood-Nimmo (2009) combines a nonlinear long-run 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 that can be decomposed as $q_t = q_0 + q_t^+ + q_t^-$, $q_t^+$ and $q_t^-$ are the partial sum processes of positive and negative changes in $q_t$ defined by $q_t^+ = \sum_{j=1}^t \Delta q_j^+$ and $q_t^- = \sum_{j=1}^t \Delta q_j^-$.

10 Though we cannot identify the size of individual transactions, Bjønnes and Rime (2005), and Reitz, Schmidt, and Taylor (2011) find that the size of the deal is relatively unimportant for pricing. Furthermore, Killeen, Lyons, and Moore (2006) construct the daily order flow measured in signed count and in value for DEM/FRF from January to April 1998, and show that the correlation between two order-flow measures is remarkably high at 0.98.
\[ \Delta p_t = \psi p_{t-1} + \theta^+ q_{t-1}^- + \theta^- q_{t-1}^+ + \sum_{j=1}^p \pi_j \Delta p_{t-j} + \sum_{j=0}^q (\varphi_j^+ \Delta q_{t-j}^- + \varphi_j^- \Delta q_{t-j}^+) + e_t, \]

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 \( \Delta q_t \). The equilibrium impacts of \( \Delta q_t^+ \) and \( \Delta q_t^- \) on \( \Delta p_t \) are captured by \( \lambda^+ = -\theta^+ / \psi \) and \( \lambda^- = -\theta^- / \psi \), respectively. The contemporaneous impacts of \( \Delta q_t^+ \) and \( \Delta q_t^- \) on \( \Delta p_t \) are captured by \( \kappa^+ = \varphi_0^+ \) and \( \kappa^- = \varphi_0^- \), respectively. Since the NARDL model in (4.2) is linear in all the parameters including the asymmetric parameters, its estimation can be achieved simply by the 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, Shin, and Smith, 2001). It nests the following special cases: first, the long-run symmetry with \( \lambda^+ = \lambda^- \); second, the short-run symmetry with a strong form of \( \varphi_j^+ = \varphi_j^- \) for all \( i = 0, ..., q \) or a weak form of \( \sum_{j=0}^q \varphi_j^+ = \sum_{j=0}^q \varphi_j^- \); and third, both the long-run and the short-run symmetries, in which case (4.2) reduces to the linear ARDL model as considered by Pesaran, Shin, and Smith (2001). All these restrictions can be easily tested using the standard Wald statistics. Hence, FX markets can be categorized into the following four types: Type (i) the price impacts of order flow on the exchange rate are asymmetric in both the short-run and the long-run; Type (ii) the impacts are asymmetric in the short run, but symmetric in the long run; Type (iii) the impacts are symmetric in the short run, but asymmetric in the long run; and Type (iv) the impacts are symmetric in both the short run and the long run.

Finally, Shin, Yu, and Greenwood-Nimmo (2009) demonstrate that the traverse between the short-run disequilibrium and the long-run steady states of the system in (4.2) can be described by the asymmetric cumulative dynamic multipliers:

\[ m^+_h = \sum_{j=0}^h \frac{\partial p_{t+j}}{\partial q_t^+}, \quad m^-_h = \sum_{j=0}^h \frac{\partial p_{t+j}}{\partial q_t^-}, \quad h = 0, 1, 2... \]

where \( m^+_h \) and \( m^-_h \) tend to the respective asymmetric long-run parameters, \( \lambda^+ \) and \( \lambda^- \), as the horizon tends to infinity. The ability of the dynamic multipliers to illuminate the traverse between the short-run disequilibrium and the steady states as well as the difference between the two steady states can prove useful in the analysis of our DAPS model. Especially, this ability can provide insights into the dynamic price adjustment process as described in Subsection 3.4.

From the dynamic multiplier analysis, we aim to address three main issues. First, what are the typical patterns of the dynamic price adjustment process towards equilibrium after underreactions and overreactions? A careful examination of this issue can reveal the nature of market disequilibrium and the feedback trading strategies of the noise and the rational traders. This important issue is rarely analyzed in the literature due to the assumption of continuous market-clearing in theoretical models and the failure to find a (symmetric) cointegrating relationship between the exchange rate and order flow in empirical studies. The second issue is whether the dynamic price adjustment processes are symmetric under buying and selling pressures. Within our 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 whether the adjustment patterns are similar across different FX markets.

\[ \sum_{j=1}^i \max(\Delta q_j, 0) \text{ and } q^-_i = \sum_{j=1}^i \Delta q^-_j = \sum_{j=1}^i \min(\Delta q_j, 0); \quad \lambda^+ \text{ and } \lambda^- \text{ are the asymmetric long-run parameters. } \]

Shin, Yu and Greenwood-Nimmo (2009) demonstrate that (4.1) can be generalized into the following asymmetric error-correction form:
4.2 Static models

For comparison purpose, we estimate the following static models and test for a long-run level relationship between the exchange rate and order flow:

\[ p_t = \lambda q_t + \xi_t, \quad (4.4) \]
\[ p_t = \lambda^+ q^+_t + \lambda^- q^-_t + \xi_t. \quad (4.5) \]

Table 7 presents the estimation results for the static symmetric model (4.4) and shows that the price impact of (cumulative) order flow on the exchange rate (the coefficient on \( q_t \)) is significant in all eight markets. Surprisingly, the price impact of order flow is negative in GBP, BEF, and ITL. Furthermore, the static symmetric regressions suffer from serial correlation in all eight markets, and from incorrect functional form in four. Table 5 provides the Engle-Granger (1987) residual-based cointegration test results for the static symmetric model. The results confirm a symmetric (linear) cointegrating relationship between the exchange rate and (cumulative) order flow in NLG only.

Table 8 reports the estimation results for the static asymmetric model (4.5). We find that the price impacts of positive and negative order flows (the coefficients on \( q^+_t \) and \( q^-_t \)) are significant and correctly signed in most cases. The only exceptions are the negative impacts of positive order flows in BEF and CHF. The static asymmetric regressions also suffer from serial correlation in all eight markets, and from incorrect functional form in four. Table 6 provides the Engle-Granger cointegration test results for the static asymmetric model, which suggests that an asymmetric cointegrating relationship between the exchange rate and order flow is confirmed in NLG only.

In summary, the estimation and test results for both static models are generally unsatisfactory. We find that the static asymmetric model (4.5) can provide weak evidence in favor of the asymmetric price impacts of positive and negative order flows since the Wald statistics strongly reject the null of \( \lambda^+ = \lambda^- \) in all eight markets. However, the Engle-Granger residual-based tests do not provide supporting evidence of a cointegrating relationship between the exchange rate and order flow, which is consistent with the finding of existing studies.

4.3 Dynamic models

We estimate the empirical specification (4.2) of our DAPS model that does not impose any symmetry restriction. Then we test the null hypotheses of no cointegration, long-run symmetry, and short-run symmetry as described in Subsection 4.1. The estimation and test results for the dynamic asymmetric model (4.2) are presented in Table 9. We find that the long-run price impacts of positive and negative order flows (the coefficients \( \lambda^+ = -\theta^+ / \psi \) and \( \lambda^- = -\theta^- / \psi \)) are correctly signed and statistically significant in almost all markets. The dynamic asymmetric regressions do not display any serial correlation in any of the eight markets, but there is weak evidence of heteroskedasticity in four markets. The adjusted \( R^2 \)s (\( \bar{R}^2 \)) range between 0.26 and 0.76. In particular, the \( \bar{R}^2 \)s for DEM and JPY equations are 0.76 and 0.66, respectively, that are remarkably higher than the corresponding \( \bar{R}^2 \)s of 0.64 and 0.46 reported in Evans

12A constant is added to all regression equations. All coefficients on order flows are multiplied by 100 for clarification, as in Evans and Lyons (2002a; b). Then, these coefficients can be interpreted as: 1000 excess selling (buying) orders decrease (increase) the exchange rates by how many percents.

13We follow the general-to-specific approach recommended by Shin, Yu and Greenwood-Nimmo (2009) to select the final lag orders for the Nonlinear (asymmetric) ARDL specification, (4.2). Specifically, we start with the maximum lag order of 14, i.e. \( p_{\text{max}} = q_{\text{max}} = 14 \), and then drop all insignificant stationary regressors sequentially. Our choice of the maximum lag order is supported by previous studies, e.g. Evans and Lyons (2005; 2006), and Reitz Schmidt, and Taylor (2011), which demonstrates that information is slowly embedded into exchange rates.
and Lyons (2002b). The $R^2$s for the equations of other FX markets are also predominantly higher than the corresponding $R^2$s reported in Evans and Lyons (2002a). This improvement clearly demonstrates that the static return regressions in Evans and Lyons (2002a; b) suffer from omitting the significant error-correction term as well as other dynamic terms.

The test results in Table 9 first, reflect that the $F$-statistics ($F_{PSS}$) strongly reject the null of no cointegration in seven markets at the 5% significance level, and in BEF at the 10% level. This finding confirms an asymmetric cointegrating relationship between the exchange rate and (cumulative) order flow in all markets. Second, the Wald statistics ($W_{SR}$ and $W_{LR}$) reject both the null of short-run symmetry and the null of long-run symmetry in 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 the Wald test results, we categorize eight markets into four types described in Subsection 4.1: DEM, JPY, BEF and ITL belong to Type (i); CHF and NLG to Type (ii); GBP and FRF to Type (iii); and none to Type (iv).

For comparison purpose, we estimate the dynamic symmetric model, i.e. the restricted version of (4.2) in which $\theta^+ = \theta^- = \theta$ and $\varphi^+_j = \varphi^-_j = \varphi_j$ for $j = 0, 1, \ldots, q$. The results are provided in Table 10. We find that the $F$-statistics of the bounds test for cointegration confirm a linear cointegrating relationship only in CHF, FRF and NLG. Importantly, most of the estimated long-run price impacts of order flow (the coefficient $\lambda = \theta/\psi$) are misleading. In particular, the long-run price impact of order flow is insignificant in DEM, JPY, and GBP, and incorrectly negative in DEM and GBP. Furthermore, in absolute terms, the error-correction coefficients (the coefficient on $p_{t-1}$) of the dynamic symmetric regressions are all considerably smaller than those of the dynamic asymmetric regressions. This finding indicates that the adjustment speed in the dynamic symmetric model is slower than that in the dynamic asymmetric model. For example, the adjustment speeds of the dynamic symmetric regressions for JPY and GBP are about 5 and 7 times slower than those of the corresponding dynamic asymmetric regressions. Surprisingly, the error-correction coefficient of the dynamic symmetric regression for DEM is positive. Therefore, the poor and misleading estimation results of the dynamic symmetric model can be attributed to the imposition of invalid symmetry restrictions in the short run and the long run.

Next, we examine the asymmetric price impacts of order flow in the dynamic asymmetric model in Table 11. The estimation results demonstrate that the long-run price impact of negative order flow is greater than that of positive positive order flow in seven markets, with the exception being NLG. The differential between the long-run price impacts of positive and negative order flows is statistically significant in six markets, with the exception being CHF. By construction of our DAPS model, the asymmetry in the long-run price impacts of positive and negative order flows implies the asymmetry in their contemporaneous price impacts (the coefficients on $\Delta q^-_t$ and $\Delta q^+_t$). From Table 9 we find that the contemporaneous price impact of negative order flow is greater than that of positive order flow in seven markets, consistent with the prediction of our DAPS model. The only exception is BEF in which none of the contemporaneous impacts is statistically significant. Finally, the speeds of adjustment towards equilibrium in the dynamic asymmetric regressions vary across markets. GBP exhibits the fastest adjustment speed, followed by NLG, FRF, and JPY. Such variation reflects different liquidity conditions in the eight markets.

In sum, we find that both the short-run and the long-run price impacts of negative order flows are significantly greater than those of positive order flows. This finding indicates that traders respond more strongly to dollar-selling pressure than they do to dollar-buying pressure. The strong evidence of the asymmetric responses of traders to buying and selling pressures together with the varying speeds of adjustment suggests that the price discovery process can be quite complicated and heterogeneous across different FX markets.
4.4 Price discovery process

The dynamic multiplier analysis enables us to examine how the prices evolve towards equilibrium under the unit impacts of the daily excess buying and selling orders (measured in thousands). We multiply the impact of selling pressure by $-1$ to highlight the difference through the net impact of buying and selling pressures. The asymmetric cumulative dynamic multiplier effects under Type (i) for all markets are plotted in Figure 4, and those under the Types suggested by the test results in Subsection 4.3 are plotted in Figure 5. Specifically, Type (ii) is suggested for CHF and NLG, Type (iii) for GBP and FRF, and Type (iv) for none of the markets. Figures 4 and 5 show that the price discovery processes in CHF and NLG are quite similar under Type (i) and Type (ii). Meanwhile, the estimation results of the dynamic asymmetric model indicates that the adjustment processes in GBP and FRF are quite different under buying and selling pressures. Hence, without loss of generality we focus on Type (i) in all eight markets.

A careful inspection of Figure 4 suggests several stylized findings. First, the net impacts in all markets, the differences between the price impacts of positive and negative order flows, are mostly negative over all horizons. The negative net impacts imply that the impact of dollar-selling pressure is stronger than that of dollar-buying pressure of the same magnitude, thus supporting the view that traders are more risk-averse to dollar-selling pressure. In particular, the long-run price impact of negative order flow is about 1.2%, 3.7%, 1.8%, 1.9%, 60%, and 10% larger than that of positive order flow in DEM, GBP, JPY, FRF, BEF, and ITL, respectively. The net impacts are negligible only in CHF and NLG. Second, we find that mispricing persists over several days in all eight markets. The degree of persistence varies across markets, depending on the nature of the mispricing condition, underreaction or overreaction. The persistent mispricing clearly indicates the biased behaviour of the noise traders and the limited arbitrage of the rational traders, as discussed in Abreu and Brunnermeier (2002, 2003), DeLong, Shleifer, Summers, and Waldmann (1990a; b), and Shleifer and Vishny (1997).

Third, we observe two typical patterns of the price discovery process, one following underreactions and the other following overreactions. Specifically, the price discovery process following underreactions is generally characterized by a sequence of small and gradual adjustments. Markets exhibiting this adjustment pattern, denoted Group 1, include DEM, CHF, BEF, and ITL. This pattern resembles Events A and C in Figure 2. Our discussion in Subsection 3.2 suggests that the persistent underreaction can curb market liquidity (decreasing habit level) and result in a persistent adjustment process. Indeed, we find that the error-correction coefficients of the dynamic asymmetric regressions for DEM, CHF, BEF, and ITL are relatively small at -0.1, -0.08, -0.16, and -0.28, respectively (see Table 9). Moreover, the gradual adjustment in Group 1 suggests that overall the positive feedback trading of the rational traders dominates and slowly pushes the prices towards their equilibrium levels, as discussed in Subsection 5.4. Meanwhile, the detractions during the adjustment process of Group 1 likely reflect the negative feedback trading of noise traders (Event C).

By contrast, the price discovery process in overreacting markets, namely GBP, JPY, FRF and NLG (Group 2), is typified by delayed overshooting and a volatile, but faster adjustment episode. Our DAPS framework suggests that the excess speculative demand associated with
overreacting condition triggers such short-run instability. This finding is consistent with the discussion in Tobin (1978), and Summers and Summers (1989) that the excess speculative demand can cause market instability. Moreover, Figure 2 displays that both the delayed overshooting and overadjusting (Events E2 and F) are clearly present in Group 2. These events likely result from the trend-chasing trading of the noise traders, as analyzed in Hong and Stein (1999), and DeLong, Shleifer, Summers, and Waldmann (1990b). Overall, it is the negative feedback trading of the rational traders that brings the overreacted prices towards equilibrium. Given the excess speculative demand in overreacting markets, traders can trade in and out of positions easily, and thus they can take larger arbitrage positions than they do in liquidity-constrained markets. Indeed, the error-correction coefficients of the dynamic asymmetric regressions for GBP, JPY, FRF, and NLG are -0.44, -0.29, -0.30, and -0.40, respectively (see Table 9) that are larger, in absolute terms, than those for Group 1 markets. This comparison supports our expectation that the adjustment speeds of Group 2 are faster than those of Group 1.

Finally, the long-run price impacts of positive and negative order flows provide the upper and the lower bounds, respectively, around which the prices fluctuate. A deviation outside these bounds indicates market overreaction and an excess speculative demand level. On the contrary, a deviation within these bounds signals market underreaction and a low speculative demand level. The different levels of speculative demand 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 bounds tend to be persistent, which is consistent with our discussion in Subsection 3.4.

5 Concluding remarks

We generalize the the portfolio shifts model of Evans and Lyons (2002a; b) by explicitly accounting for persistent mispricing and for an asymmetric relationship between the exchange rate and order flow. Our model nests the portfolio shifts model of Evans and Lyons (2002b) as a special case in which the price impact of order flow is symmetric and the market is always in equilibrium. Using the Reuters D2000-1 dataset for eight currency spot markets, we find overwhelming evidence of an asymmetric cointegrating relationship between the exchange rate and order flow. In particular, the price impact of dollar-selling pressure is stronger than that of dollar-buying pressure, indicating that traders react more strongly to the unfavorable information for the dollar than they do to the favorable one. This result suggests that neglecting the asymmetric association between the exchange rate and order flow can be an important reason for the inconclusive empirical evidence of an equilibrium relationship between these two variables in previous studies.

Our finding of the asymmetric price impacts of dollar-selling and dollar-buying pressures contrasts with the supposed symmetry in currency markets. In these markets, traders exchange one currency for another and buying pressure of one currency means selling pressure of another. Hence, currency markets are supposed to be structurally symmetric. Then, given the documented stronger reaction of markets to unfavorable information than to favorable information (e.g. Andersen, Bollerslev, Diebold, and Vega, 2003), why do traders react more strongly to unfavorable information for the dollar than they do to unfavorable information for any other currency? The answer is likely because the dollar is the most widely used and most important currency in international financial markets (e.g. Thimann, 2008), and thus unfavorable information for the dollar would generate a stronger and wider reaction than unfavorable information for any other currency would. As a result, the supposed symmetry in FX markets need not hold due to the different importance of different currencies in international financial markets.

Next, our dynamic multiplier analysis show that the short-run movements of exchange rates deviate considerably from their long-run equilibrium relationship with order flow, reflecting the biased behavior of the noise traders and the limited arbitrage of the rational traders. Furthermore, we observe two common patterns of the price discovery process in FX markets. Specifically,
underreacting markets adjust towards equilibrium gradually, which likely represents the dominant positive feedback trading of the rational traders. On the contrary, overreacting markets display delayed overshooting and volatile adjustments. We argue that such a volatile episode is attributable to the excess speculative demand caused by overreactions and by the trend-chasing trading of the noise traders (e.g. DeLong, Shleifer, Summers, and Waldmann, 1990b; Hong and Stein, 1999). The instability in liquid markets is well supported by the traditional economic view of liquidity (Keynes, 1935; Tobin, 1978). However, the instability in overreacting markets only exists in the short run and overreactions are corrected relatively quicker than underreactions are.

Our finding of the different adjustment patterns in underreacting and overreacting markets provides policymakers with guidance for the timing and magnitude of intervention. In particular, overreacting markets are filled with excess speculative demands and active noise traders, hence interventions with large magnitude to correct large price distortions could further destabilize the markets. Meanwhile, underreacting markets are short of liquidity, and thus a moderate injection of liquidity could push these markets towards equilibrium faster. In general, our study provides a better understanding of how the exchange rate is determined in the micro, information-driven environment.

### A Appendix: Dynamic price discovery process

We examine in details how the market adjusts dynamically towards equilibrium under our DAPS framework. For simplicity, we suppose that the market is in disequilibrium in period $t$ and returns to equilibrium after $k$ ($\leq T - t$) periods, and that the only new information is given by the deviation of the price from fundamentals and the unobservable inventory imbalances of the dealers in period $t$. Over $k$ periods, mispricing is removed and the dealers clear their inventory imbalances. During the adjustment process, all the dealers quote common prices in three trading rounds to avoid arbitrage opportunities. The quoting strategies of the dealers are written as (see Evans and Lyons, 1999; 2002a)

\[
P_{t+j}^1 = P_{t+j}^2 = P_{t+j-1}^3 + \Delta R_{t+j}, \tag{A.1}
\]

\[
P_{t+j}^3 = P_{t+j}^2 + \lambda \Delta Q_{t+j}. \tag{A.2}
\]

Combining (A.1) and (A.2), we obtain:

\[
P_{t+j}^3 = P_{t+j-1}^3 + \Delta R_{t+j} + \lambda \Delta Q_{t+j}. \tag{A.3}
\]

We discuss, in details, the adjustment processes under buying pressure (up market) only. The adjustment processes under selling pressure (down market) can be analyzed similarly with the opposite price movements.

#### A.1 Price discovery in underreacting markets

The market disequilibrium in period $t$, caused by underreaction, can be expressed as (see (3.5))

\[
C_t^{1+} + C_t^{-} = \delta_t^{U+}, \tag{A.4}
\]

where $\delta_t^{U+} > 0$ is the market imbalance (excess buying orders) in period $t$. The dealers have to hold this undesired imbalance due to the insufficient speculative demand of the public in round 3 of period $t$. Then, the disequilibrium price level can be written as

\[
P_{t}^{3+} = R_{t}^{+} + \lambda^{+} Q_{t}^{+} - \frac{\delta_{t}^{U+}}{\gamma_{+}}. \tag{A.5}
\]
Defining the equilibrium price by
\[ P_t^{*+} = R_t^+ + \lambda^+ Q_t^{*+}, \]  
where the superscript \( ^{*+} \) indicates the equilibrium level, we can express the mispricing as
\[ P_t^{*+} - P_t^{st+} = \lambda^+(Q_t^{*+} - Q_t^+) + \frac{\delta U^+}{\gamma^+} > 0. \]  

(A.7) shows that the mispricing consists of the two terms: \( \lambda^+(Q_t^{*+} - Q_t^+) > 0 \) represents the deviation of the price from fundamentals, and \( \delta U^+ / \gamma^+ > 0 \) capture the unobserved, additional price concession (premium) required to compensate for the insufficient speculative demand (low liquidity) in period \( t \).

We now discuss the possible trading outcomes in period \( t + 1 \) in the presence of both the rational and the noise traders. Denote the aggregate trade orders of the rational and the noise traders in round 1 by \( F_t \) and \( N_t (\neq 0) \), respectively. Notice that \( F_t \) is always equilibrium-driven while \( N_t \) can move in the same direction with or in the opposite direction to \( F_t \). Thus, the absolute values of \( F_t \) and \( N_t \) represent the relative strengths of the rational and the noise traders in period \( t \). Let \( a_t \) be the time-varying probability that \( |F_t| < |N_t| \) and \( b_t \) be the time-varying probability that \( F_t \) and \( N_t \) are of the same direction, i.e. both the rational and the noise traders buy or sell the risky asset. (A.7) suggests that the rational traders will buy the risky asset to push its price towards the equilibrium level while the noise traders can buy or sell the risky asset. Depending on the relative strengths of the two types of traders, \( a_t \), and the trading strategies of noise traders, \( b_t \), we summarize four possible outcomes in round 1 of period \( t + 1 \) in Table 2.

<table>
<thead>
<tr>
<th>Relative strength</th>
<th>Outcome</th>
<th>Probability</th>
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<tr>
<td>1. (</td>
<td>F_{t+1}</td>
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<tr>
<td>2a. ( F_{t+1}^+ + N_{t+1}^+ = C_{t+1}^+ )</td>
<td>( (1 - a_{t+1})b_{t+1} )</td>
<td>( (1 - a_{t+1})(1 - b_{t+1}) )</td>
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<tr>
<td>2b. ( F_{t+1}^+ + N_{t+1}^+ = C_{t+1}^+ )</td>
<td>( (1 - a_{t+1})b_{t+1} )</td>
<td>( (1 - a_{t+1})(1 - b_{t+1}) )</td>
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\*\( C_{t+1} \) 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, \( C_{t+1}^{+} \) denotes that they are of opposite directions with the dominance of the rational (noise) traders. \( Pr(|F_{t+1}| < |N_{t+1}|) = a_{t+1} \) and \( Pr(N_{t+1}^+ = b_{t+1}) \).

Table 2: Trading outcomes in underreacting market

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 overshooting (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 who dominates the market \( (a_t) \). Hence, the higher the probability that the noise traders follow the trading strategy of the rational traders (say, \( b_t > 0.5 \)), the more likely Event B is to occur. Second, if the noise traders mostly adopt the opposite trading strategy to the rational traders, i.e. \( b_t \) is quite low, then the market experiences 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. the probability.

\[ ^{16}\text{Clearly, no adjustment is made if } F_{t+1} = -N_{t+1} \text{ as in Case 2b.} \]
Moreover, the overall adjustment patterns associated with Events A and B are characterized by positive feedback trading that mainly stabilizes the market. By contrast, Event C implies the dominant negative feedback trading of the noise traders that destabilizes the market by moving the price further away from its equilibrium.

The adjustments in period \( t + j \) for \( j = 2, \ldots, k \), can be analyzed similarly. When the market returns to equilibrium in period \( t + k \), the two following conditions are satisfied:

\[
P_{t+k}^3 = P_t^{++} \quad \text{and} \quad \sum_{j=0}^{k} (C_{t+j}^1 + C_{t+j}^3) = 0. \tag{A.8}
\]

Using the first condition of (A.8) in (A.7), we obtain:

\[
P_{t+k}^3 - P_t^{3+} = \lambda^+ (Q_t^{+*} - Q_t^+) + \frac{\delta_U^+}{\gamma^+}. \tag{A.9}
\]

Using the identity, \( P_{t+k}^3 = \sum_{j=1}^{k} (\Delta R_{t+j} + \lambda^+ \Delta Q_{t+j}) \), we can rewrite (A.9) as

\[
\sum_{j=1}^{k} (\Delta R_{t+j} + \lambda^+ \Delta Q_{t+j}) = \lambda^+ (Q_t^{+*} - Q_t^+) + \frac{\delta_U^+}{\gamma^+}. \tag{A.10}
\]

(A.10) shows that the cumulative adjusted risk premia over \( k \) periods (the left-hand side component) is equal to (i) the price deviation from the fundamental value, denoted by \( \lambda^+ (Q_t^{+*} - Q_t^+) \) and (ii) the unobserved price concession required in period \( t \), denoted by \( \frac{\delta_U^+}{\gamma^+} \), 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 integrated into the price after \( k \) trading periods. Furthermore, using (A.4), the second condition of (A.8) can be expressed as

\[
\sum_{j=1}^{k} (C_{t+j}^1 + C_{t+j}^3) = -\delta_U^+, \tag{A.11}
\]

which shows that the dealers successfully clear their period-\( t \) imbalances over \( k \) periods.

### A.2 Price discovery in overreacting markets

The market disequilibrium in period \( t \), caused by overreaction, can be expressed as (see (3.5)):

\[
C_t^{1+} + C_t^{3-} = \delta_U^-, \tag{A.12}
\]

where \( \delta_U^- < 0 \) is the market imbalance (excess selling orders). The dealers have to hold this imbalance due to excess speculative demand. Then, the disequilibrium price level is written as

\[
P_t^{3+} = R_t^+ + \lambda^+ Q_t^+ - \delta_U^- / \gamma^+. \tag{A.13}
\]

Using the equilibrium price level in (A.6), we can express the mispricing as

\[
P_t^{++} - P_t^{3+} = \lambda^+ (Q_t^{+*} - Q_t^+) + \frac{\delta_U^-}{\gamma^+} < 0. \tag{A.14}
\]

(A.14) shows that the price in round 3 of period \( t \), \( P_t^{3+} \), deviates from fundamentals by \( \lambda^+ (Q_t^{+*} - Q_t^+) < 0 \), and includes an additional concession of \( \frac{\delta_U^-}{\gamma^+} < 0 \) that is more than required when the speculative demand is excessive.

(A.14) suggests that the rational traders will sell the risky asset to reduce its price to the equilibrium level while the noise traders either buy or sell the risky asset. Depending on the relative strength of the two types of traders, \( a_t \), and the trading strategies of the noise traders, \( b_t \), we summarize four possible outcomes in round 1 of period \( t + 1 \) in Table 3.

The four outcomes in Table 3 can be grouped into three events as follows:
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<td></td>
<td>$a_{t+1}b_{t+1}$</td>
<td>$a_{t+1} (1 - b_{t+1})$</td>
</tr>
<tr>
<td>2. $</td>
<td>F_{t+1}</td>
<td>\geq</td>
</tr>
<tr>
<td></td>
<td>$F_{t+1}^- + N_{t+1}^+ = C_{t+1}^+$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$F_{t+1}^+ + N_{t+1}^- = C_{t+1}^-$</td>
<td></td>
</tr>
</tbody>
</table>

* $C_{t+1}$ 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, $C_{t+1}^+$ denotes that they are of opposite directions with the dominance of the rational (noise) speculators. $Pr(|F_{t+1}| < |N_{t+1}|) = a_{t+1}$ and $Pr(N_{t+1}^-) = b_{t+1}$.

Table 3: Trading outcomes in overreacting market

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

We have the following scenarios. When most noise traders follow the equilibrium-driven trading strategy of the rational traders, i.e. $b_t$ is relatively high, the market is likely to experience Event $E$. On the contrary, when more noise traders adopt the counter-equilibrium trading strategy, i.e. $b_t$ is relatively low, Event $E$ (Event $F$) is more likely to occur if the rational (noise) traders prevail. The overall adjustment patterns associated with Events $D$ and $E$ display the negative feedback trading strategy that mainly stabilize the market. Event $F$, however, implies the dominant positive feedback trading of the noise traders that destabilizes 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 (A.8) are satisfied. Using similar derivations of (A.10) and (A.11), we obtain:

$$\sum_{j=1}^{k} (\Delta R_{t+j} + \lambda^+ \Delta Q_{t+j}) = \lambda^+ (Q_{t+k}^+ - Q_{t}^+) + \frac{\delta U^-}{\gamma^+},$$

(A.15)

$$\sum_{j=1}^{k} (C_{t+j}^1 + C_{t+j}^2) = -\delta^U_t.$$

(A.16)

(A.15) indicates that the market returns to equilibrium only if both the deviation of the price from fundamentals and the surplus price concession in period $t$ are fully discounted from the price after $k$ trading periods. (A.16) suggests that the public fully reabsorbs the risky imbalances of the dealers over $k$ periods.
B Appendix: Tables and figures

| Mkt. | ∆qₗ | ∆qₗ⁻ | ∑∆qₗ | ∑∆qₗ⁻ | ∑|∆qₗ| | ∑∆qₗ | ∑∆qₗ⁻ | ∑∆pₗ |
|------|------|------|-------|-------|-------|-------|-------|-------|
| 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  | -1466 | -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 |

*The # denote the number of observations. ∆q₀ denotes ∆q = 0.

Table 4: Summary statistics of the Reuters D2000–1 dataset

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

*The Engle-Granger Dicky-Fuller (EGDF) regressions include an intercept but not a trend. The 95% critical value for the EGDF statistic is -3.419. The Akaike information criterion and the Bayesian Schwarz criterion often suggest the lag order between 0 and 2.

Table 5: Engle-Granger cointegration test results for the static symmetric model

<table>
<thead>
<tr>
<th>Lag order</th>
<th>DEM</th>
<th>GBP</th>
<th>JPY</th>
<th>CHF</th>
<th>FRF</th>
<th>BEF</th>
<th>ITL</th>
<th>NLG</th>
</tr>
</thead>
</table>

*The Engle-Granger Dicky-Fuller (EGDF) regressions include an intercept but not a trend. The 95% critical value for the EGDF statistic is -3.857. The Akaike information criterion and the Bayesian Schwarz criterion often suggest the lag order between 0 and 2.

Table 6: Engle–Granger cointegration test results for the static asymmetric model
<table>
<thead>
<tr>
<th>Regressor</th>
<th>DEM</th>
<th>GBP</th>
<th>JPY</th>
<th>CHF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t-ratio</td>
<td>Coefficient</td>
<td>t-ratio</td>
</tr>
<tr>
<td>$q_t$</td>
<td>3.50</td>
<td>11.00</td>
<td>-1.30</td>
<td>-5.081</td>
</tr>
<tr>
<td>Constant</td>
<td>0.42</td>
<td>308.2</td>
<td>-0.43</td>
<td>-274.7</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.600</td>
<td>0.237</td>
<td>0.570</td>
<td>0.512</td>
</tr>
<tr>
<td>$\chi^2_{SC}$</td>
<td>74.092</td>
<td>63.950</td>
<td>66.644</td>
<td>73.522</td>
</tr>
<tr>
<td>$\chi^2_{FF}$</td>
<td>.44256</td>
<td>.28204</td>
<td>9.3695</td>
<td>53.639</td>
</tr>
<tr>
<td>$\chi^2_N$</td>
<td>12.254</td>
<td>6.1213</td>
<td>4.5742</td>
<td>7.3636</td>
</tr>
<tr>
<td>$\chi^2_{HE}$</td>
<td>.01214</td>
<td>18.492</td>
<td>3.3224</td>
<td>.35658</td>
</tr>
</tbody>
</table>

(a) DEM, GBP, JPY, CHF

<table>
<thead>
<tr>
<th>Regressor</th>
<th>FRF</th>
<th>BEF</th>
<th>ITL</th>
<th>NLG</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t-ratio</td>
<td>Coefficient</td>
<td>t-ratio</td>
</tr>
<tr>
<td>Constant</td>
<td>1.63</td>
<td>1982.</td>
<td>3.45</td>
<td>2152.</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.809</td>
<td>0.681</td>
<td>0.481</td>
<td>0.880</td>
</tr>
<tr>
<td>$\chi^2_{SC}$</td>
<td>59.745</td>
<td>62.148</td>
<td>54.247</td>
<td>39.935</td>
</tr>
<tr>
<td>$\chi^2_{FF}$</td>
<td>7.1684</td>
<td>7.0055</td>
<td>2.1256</td>
<td>2.0973</td>
</tr>
<tr>
<td>$\chi^2_N$</td>
<td>3.5194</td>
<td>6.5305</td>
<td>1.4867</td>
<td>2.5334</td>
</tr>
<tr>
<td>$\chi^2_{HE}$</td>
<td>2.8965</td>
<td>1.8340</td>
<td>1.3314</td>
<td>1.0626</td>
</tr>
</tbody>
</table>

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

(b) FRF, BEF, ITL, NLG

Table 7: Estimation and test results for the static symmetric model
<table>
<thead>
<tr>
<th>Regressor</th>
<th>DEM</th>
<th>GBP</th>
<th>JPY</th>
<th>CHF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t–ratio</td>
<td>Coefficient</td>
<td>t–ratio</td>
</tr>
<tr>
<td>( q_t^+ )</td>
<td>1.60</td>
<td>7.038[.000]</td>
<td>0.50</td>
<td>4.000[.000]</td>
</tr>
<tr>
<td>( q_t^- )</td>
<td>2.40</td>
<td>11.89[.000]</td>
<td>4.10</td>
<td>14.52[.000]</td>
</tr>
<tr>
<td>Constant</td>
<td>0.43</td>
<td>331.0[.000]</td>
<td>-0.41</td>
<td>-410.[.000]</td>
</tr>
</tbody>
</table>

Adj. \( R^2 \) 0.870  0.881  0.854  0.620  
\( \chi^2_{SC} \)  67.770[.000]  36.379[.000]  47.625[.000]  67.416[.000]  
\( \chi^2_{FE} \)  32.618[.000]  .83368[.361]  9.0461[.003]  52.874[.000]  
\( \chi^2_{N} \)  4.0635[.131]  .25518[.880]  3.6603[.160]  2.2071[.332]  
\( \chi^2_{HE} \)  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

<table>
<thead>
<tr>
<th>Regressor</th>
<th>FRF</th>
<th>BEF</th>
<th>ITL</th>
<th>NLG</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t–ratio</td>
<td>Coefficient</td>
<td>t–ratio</td>
</tr>
<tr>
<td>( q_t^+ )</td>
<td>5.80</td>
<td>11.36[.000]</td>
<td>-6.60</td>
<td>-1.75[.083]</td>
</tr>
<tr>
<td>( q_t^- )</td>
<td>7.80</td>
<td>20.16[.000]</td>
<td>11.60</td>
<td>1.318[.191]</td>
</tr>
<tr>
<td>Constant</td>
<td>1.64</td>
<td>1100.[.000]</td>
<td>3.46</td>
<td>2097.[.000]</td>
</tr>
</tbody>
</table>

Adj. \( R^2 \) 0.906  0.721  0.939  0.898  
\( \chi^2_{SC} \)  50.724[.000]  62.317[.000]  34.044[.000]  29.863[.000]  
\( \chi^2_{FE} \)  1.1769[.278]  4.9194[.027]  5.0052[.025]  .02868[.866]  
\( \chi^2_{N} \)  5.5652[.062]  4.3073[.116]  5.3303[.070]  1.6195[.445]  
\( \chi^2_{HE} \)  10.921[.001]  .77754[.378]  .19059[.662]  .98143[.322]  
WALD  83.863[.000]  12.434[.000]  594.14[.000]  15.023[.000]  

*WALD denotes the Wald statistic for testing the null hypothesis of \( \lambda^+ = \lambda^- \); the Wald statistic follows a \( \chi^2 \) distribution under the null. See also the footnotes of Table 7.

(b) FRF, BEF, ITL, NLG

Table 8: Estimation and test results for the static asymmetric model
<table>
<thead>
<tr>
<th>Reg.</th>
<th>Coeff.</th>
<th>t-ratio</th>
<th>Reg.</th>
<th>Coeff.</th>
<th>t-ratio</th>
<th>Reg.</th>
<th>Coeff.</th>
<th>t-ratio</th>
<th>Reg.</th>
<th>Coeff.</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td></td>
<td></td>
<td>GBP</td>
<td></td>
<td></td>
<td>JPY</td>
<td></td>
<td></td>
<td>CHF</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( p_{t-1} )</td>
<td>-0.10</td>
<td>-1.92</td>
<td>0.59</td>
<td>( q_{t-1}^{+} )</td>
<td>0.35</td>
<td>2.92</td>
<td>0.05</td>
<td>( q_{t-1}^{-} )</td>
<td>0.47</td>
<td>3.15</td>
<td>0.03</td>
</tr>
<tr>
<td>( \lambda^{+} )</td>
<td>3.32</td>
<td>2.28</td>
<td>0.02</td>
<td>( \lambda^{-} )</td>
<td>4.44</td>
<td>3.19</td>
<td>0.02</td>
<td>( \Delta p_{t-2} )</td>
<td>-12.78</td>
<td>-2.00</td>
<td>0.05</td>
</tr>
<tr>
<td>( \Delta q_{t-1}^{+} )</td>
<td>-1.25</td>
<td>-3.68</td>
<td>0.01</td>
<td>( \Delta q_{t-2}^{+} )</td>
<td>0.75</td>
<td>1.96</td>
<td>0.05</td>
<td>( \Delta q_{t-6}^{+} )</td>
<td>-0.68</td>
<td>-1.67</td>
<td>0.10</td>
</tr>
<tr>
<td>( \Delta q_{t-14}^{-} )</td>
<td>2.70</td>
<td>7.51</td>
<td>0.00</td>
<td>( \Delta q_{t-1}^{-} )</td>
<td>0.94</td>
<td>2.32</td>
<td>0.02</td>
<td>( \Delta q_{t-12}^{-} )</td>
<td>-0.51</td>
<td>-1.92</td>
<td>0.59</td>
</tr>
<tr>
<td>( \Delta q_{t-13}^{-} )</td>
<td>0.63</td>
<td>2.32</td>
<td>0.02</td>
<td>( \Delta q_{t-7}^{-} )</td>
<td>-2.61</td>
<td>-2.77</td>
<td>0.08</td>
<td>( \Delta q_{t-14}^{-} )</td>
<td>-1.68</td>
<td>-2.45</td>
<td>0.17</td>
</tr>
<tr>
<td>( \text{Const.} )</td>
<td>0.04</td>
<td>2.00</td>
<td>0.05</td>
<td>( \text{Const.} )</td>
<td>-0.18</td>
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<td>( \text{Const.} )</td>
<td>1.38</td>
<td>3.73</td>
<td>0.00</td>
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</table>

| Adj. \( R^2 \) | 0.765 | Adj. \( R^2 \) | 0.449 | Adj. \( R^2 \) | 0.668 | Adj. \( R^2 \) | 0.730 |

\( \chi^2_C \) 1.9327[1.64] \( \chi^2_C \) .29421[.588] \( \chi^2_C \) .34494[.557] \( \chi^2_C \) .39673[.529]
\( \chi^2_F \) 9.1477[.002] \( \chi^2_F \) .44313[.506] \( \chi^2_F \) .02074[.885] \( \chi^2_F \) 4.2746[.039]
\( \chi^2_N \) 3.7830[.151] \( \chi^2_N \) 13.530[.001] \( \chi^2_N \) .37789[.828] \( \chi^2_N \) .27810[.870]
\( \chi^2_H \) 5.7783[.016] \( \chi^2_H \) 1.8715[.171] \( \chi^2_H \) 1.9015[.168] \( \chi^2_H \) 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] \( W_{LR} \) 0.725[.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...
Table 9: Estimation and test results of the dynamic asymmetric model

<table>
<thead>
<tr>
<th></th>
<th>FRF</th>
<th></th>
<th>BEF</th>
<th></th>
<th>ITL</th>
<th></th>
<th>NLG</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
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<td>Coef.</td>
<td>t-ratio</td>
<td></td>
<td>Reg.</td>
<td>Coef.</td>
<td>t-ratio</td>
<td></td>
</tr>
<tr>
<td>p_{t-1}</td>
<td>-0.30</td>
<td>-3.90</td>
<td>[0.000]</td>
<td></td>
<td>p_{t-1}</td>
<td>-0.16</td>
<td>-3.17</td>
<td>[0.002]</td>
</tr>
<tr>
<td>q_{t-1}^-</td>
<td>1.39</td>
<td>1.69</td>
<td>[0.095]</td>
<td></td>
<td>q_{t-1}^-</td>
<td>3.34</td>
<td>1.72</td>
<td>[0.090]</td>
</tr>
<tr>
<td>q_{t-1}^+</td>
<td>1.97</td>
<td>2.58</td>
<td>[0.012]</td>
<td></td>
<td>q_{t-1}^+</td>
<td>15.34</td>
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<td>[0.009]</td>
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<tr>
<td>\lambda^-</td>
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<td>2.33</td>
<td>[0.022]</td>
<td></td>
<td>\lambda^-</td>
<td>19.88</td>
<td>1.50</td>
<td>[0.138]</td>
</tr>
<tr>
<td>\lambda^+</td>
<td>6.51</td>
<td>5.31</td>
<td>[0.000]</td>
<td></td>
<td>\lambda^+</td>
<td>80.42</td>
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<td>[0.013]</td>
</tr>
<tr>
<td>\Delta q_{t-1}^+</td>
<td>5.47</td>
<td>1.96</td>
<td>[0.054]</td>
<td></td>
<td>\Delta p_{t-5}</td>
<td>30.26</td>
<td>2.73</td>
<td>[0.009]</td>
</tr>
<tr>
<td>\Delta q_{t-5}^-</td>
<td>1.88</td>
<td>1.04</td>
<td>[0.298]</td>
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<td>\Delta p_{t-8}^-</td>
<td>26.28</td>
<td>2.61</td>
<td>[0.011]</td>
</tr>
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<td>\Delta q_{t-6}^-</td>
<td>3.28</td>
<td>1.85</td>
<td>[0.068]</td>
<td></td>
<td>\Delta q_{t-9}^-</td>
<td>25.42</td>
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<td>[0.000]</td>
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<td>\Delta q_{t-9}^-</td>
<td>13.95</td>
<td>1.63</td>
<td>[0.109]</td>
</tr>
<tr>
<td>\Delta q_{t-11}^-</td>
<td>4.20</td>
<td>2.68</td>
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(b) FRF, BEF, ITL, NLG
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Adjusted $R^2$: 0.693  0.327  0.465  0.671

χ² SC: 0.04999[.823]  1.7315[.188]  0.01720[.896]  0.01279[.910]
χ² FF: 1.6536[.198]  0.70431[.401]  2.1508[.142]  9.7991[.002]
χ² N: 0.82083[.663]  68.871[.000]  8.8398[.012]  0.1620[.992]
χ² HE: 5.2185[.022]  0.91022[.340]  0.57848[.447]  15.820[.000]

$F_{PSS}$: 2.137  1.837  0.762  8.621

(a) DEM, GBP, JPY, CHF

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...continued from previous page

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* $\lambda$ stands for the long-run coefficient on cumulative order flow, and is obtained by $\lambda = -\theta/\psi$. $F_{PSS}$ is the $F$-statistic testing the null hypothesis of no cointegration against the alternative of a (symmetric) cointegration; the associated nonstandard critical values (for the case with an 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 Pesaran, Shin, and Smith, 2001); the null hypothesis of no cointegration is rejected if the $F$-statistic is greater than the critical value. See also the footnotes of Table 7.

(b) FRF, BEF, ITL, NLG

Table 10: Estimation and test results of the dynamic symmetric model
Figure 3: Bilateral exchange rates and cumulative order flows
Figure 4: Dynamic multiplier effects under Type (i) (asymmetry long-run and short-run)
Figure 5: Dynamic multiplier effects under suggested types
References


