Liquidity and Uncertainty Dependent Order Flow Effects in the Foreign Exchange Market: an Empirical Investigation

A Microstructure Approach to Exchange Rate Modeling

Hong Xu

Thesis for the degree
Master of Economic Theory and Econometrics

Department of Economics
University of Oslo

May 2011

Preface

This thesis marks the ending of a five year program at the University of Oslo, qualifying to the degree *Master of Economic Theory and Econometrics*. The process of writing this thesis has been a valuable and rewarding experience. The Department of Economics at University of Oslo has provided me with financial support for this thesis, which I am grateful for.

The greatest acknowledgments are reserved for my two supervisors; Dagfinn Rime, Senior Advisor at Norges Bank and Ragnar Nymoen, Professor at the University of Oslo. Both have provided me with advices, motivation and answers to my questions. A special thanks to Dagfinn is deserved, who introduced me to microstructure theory and provided me with the idea for this thesis. Data was kindly provided by Dagfinn Rime and Hans Jørgen Tranvåg, PhD student at the Norwegian University of Science and Technology (NTNU).

I am also grateful to colleagues at Norges Bank for providing a great working environment during the time I worked there. Lastly, my family deserves gratitude for always supporting my decisions through the years.

Any remaining errors and inaccuracies in this thesis are my own responsibility.

May 2011,

Hong Xu

2011

Liquidity and Uncertainty Dependent Order Flow Effects in the Foreign Exchange Market: an Empirical Investigation

Hong Xu

http://www.duo.uio.no/

Press: Reprosentralen, Universitetet i Oslo

Summary

In this thesis I try to model exchange rate fluctuations using microstructure theory. While the classical macroeconomic models of exchange rates have shown to have little or no support at frequencies higher than semiannual (Rime and Sojli, 2006), microstructure models have proved successful in explaining exchange rate movements in relative high frequent data (daily and weekly frequency). Recent literature have attempted to apply microstructure in order to explain exchange rate movements at longer horizons in order to fill the hole which macroeconomic models have proved unable to explain. Chinn and Moore (2010) used monthly data to show that order flow does have explanatory power for exchange rate fluctuations at this level as well. The authors also found cointegrating relationship between order flows and exchange rates, confirming that the effect of order flow is persistent.

This thesis is an extension to the work done at this level of frequency. I utilize two microstructure models in order to explain monthly exchange rate fluctuations for four major exchange rates. Order flows are created from foreign exchange trade statistics published in the Treasury Bulletin. Since literature and theory have shown that the price impact of order flow is dependent on market conditions, I try to control for this variability by adjusting the order flows. Building on theoretical foundations explained in Killeen et al. (2006), I therefore choose to adjust the order flows for uncertainty and liquidity. Furthermore, an attempt to control for hedging by including net option positions into the models is also provided. The Johansen trace test is applied in order to test for cointegration relationships between order flows and exchange rates.

The results obtained in this thesis show that adjusted order flow provides better in-sample fit compared with unadjusted order flow. The results also points towards an "undershooting" adjustment mechanism for the exchange rates as the long run price impact are larger than the short run impact.

The thesis is organized in following manner; chapter 2 outlines two different approaches to exchange rate modeling, the classical way with macroeconomic "fundamentals" and the microstructure approach which highlights agents heterogeneity and information superiority. The role of order flow in this setting is explained and also why it is an important determinant for explaining exchange rate fluctuations. Also included are some important facts about the exchange rate market structure. Chapter 3 contains a brief, but intuitive explanation of the two

models used in this thesis; the Portfolio Shift model and the Liquidity Shock model. Chapter 4 gives a thorough description of the data series used in this thesis. An explanation of how I create order flow series is also provided. Furthermore, the times series properties for the dataset are tested for and discussed. Chapter 5 presents the results found in this thesis. Section 5.1 deals with econometric results[1] from the Portfolio Shift model with various sorts of proxies for order flow. Section 5.2 show results from Johansen cointegration testing for both the models. Vector Error Correction Models based on the Liquidity Shock model are also estimated for each of the exchange rates. Chapter 6 concludes and proposes some potential extensions to this thesis.

[1] Estimations and other econometric results in this thesis have been done with the statistical software EViews, version 7.1. More information about the software package can be found at www.eviews.com.

Contents

1 Introduction 1

2 Different approaches to exchange rate modeling 4

2.1 The macro approach 4

2.2 The microstructure approach 5

2.2.1 The importance of private information 5

2.2.2 Foreign exchange market structure 7

2.2.3 Order flow as information aggregator 8

3 Models 11

3.1 Portfolio Shift model 11

3.2 Liquidity Shock model 13

4 Data 16

4.1 Exchange rate positions and net options 17

4.1.1 Creating order flows from exchange rate positions 17

4.1.2 Order flow 19

4.1.3 Net option positions 20

4.2 Exchange rates 23

4.3 Interest rates 24

4.4 Other data 25

4.4.1 Money supply 25

4.4.2 Industrial production 27

4.4.3 Consumer prices 27

5 Empirical results 29

5.1 Empirical results for the Portfolio Shift model 29

5.1.1 Portfolio Shift model with unadjusted order flow 30

5.1.2 Portfolio Shift model with adjusted order flow 34

Uncertainty adjustment by spot range 35

Price disagreement adjustment by volume 37

5.1.3 Effect of including net options 41
5.2 Testing for cointegration 45
5.2.1 Portfolio Shift model 46
5.2.2 Liquidity Shock model 47
5.2.3 VECM estimation results for Liquidity Shock model 49

6 Conclusions 55

References 57

A Data 61
A.1 Descriptive statistics 61
A.2 Graphs 63

B Basic time series econometrics 68
B.1 Unit roots and non-stationary variables 68
B.2 Cointegration 71
B.3 Vector Error Correction Models and Johansen test 72
B.4 Cointegration test results 76

C Regressions and test diagnostics 78
C.1 Basic theory of regression diagnostics 78
Jarque-Bera test for normality 78
Lagrange Multiplier test for autocorrelation 78
White test for heteroskedasticity 79
ARCH test for autoregressive conditional heteroskedasticity 79
C.2 Extra regressions 81
C.3 Regression diagnostics 83

D Derivations 87
D.1 Liquidity Shock model 87

List of Tables

Table 1: ADF test results for order flows 20
Table 2: ADF test results for net option positions 22
Table 3: Correlation coefficients between order flow and net option positions 22
Table 4: ADF test results for the exchange rates 23
Table 5: ADF test results for Δlog(exchange rates) 24
Table 6: ADF test results for the interest rate differences 25
Table 7: ADF test results for money supply differences 26
Table 8: ADF test results for industrial production differences 27
Table 9: ADF test results for consumer price index differences 28
Table 10: Portfolio Shift model estimation output, model [1] – [4] 32
Table 11: ADF test results for adjusted order flows 38
Table 12: Portfolio Shift model estimation output, model [2-2] – [4-2] 39
Table 13: ADF test results for adjusted net flows 42
Table 14: Portfolio Shift model estimation output, model [5] – [7] 43
Table 15: ADF test results for cumulative adjusted net flows 46
Table 16: Number of cointegrating relationships for Portfolio Shift model 47
Table 17: Number of cointegrating relationships for Liquidity Shock model 48
Table 18: Cointegrating vectors from Johansen procedure 50
Table 19: VECM estimation results for the Liqudity Shock model 53
Table A.1: Descriptive statistics for order flows 61
Table A.2: Descriptive statistics for net option positions 61
Table A.3: Descriptive statistics for the exchange rates 62
Table A.4: Descriptive statistics for the interest differentials 62
Table B.1: Critical values for the Dickey-Fuller test 70
Table B.2: Johansen trace test for Portfolio Shift model 76
Table B.3: Johansen trace test for Liquidity Shock model 77
Table C.1: Estimation for model [5] – [7] with adjusted net option included separately 81
Table C.2: Dynamic OLS (DOLS) estimation results for USD/JPY 82
Table C.3: Regression diagnostics for model [1]-[4] 83
Table C.4: Regression diagnostics for model [2-2]-[4-2] 84
Table C.5: Regression diagnostics for model [5]-[7] 85

List of Figures

Figure 1: Illustration of different approaches to exchange rate modeling 10
Figure 2: Timing for the Portfolio Shift model 13
Figure 3: Order flows 19
Figure 4: Net option positions 21
Figure 5: Comparison of R-squared from rolling regressions with spot range 37
Figure 6: Cointegrating relationships 52
Figure A.1: Exchange rates 63
Figure A.2: Interest differences 64
Figure A.3: Money supply 65
Figure A.4: Industrial production 65
Figure A.5: Consumer price index 66
Figure A.6: Spot range for exchange rates 67
Figure C.1: Recursive estimates of adjusted net flow in model [7]. 86

1 Introduction

The foreign exchange market with an average daily turnover of 4 trillion US dollars as of April 2010 is the biggest financial market measured by volume. The last decade has witnessed a huge increase in trading volume, resulting in a 160% increase in the daily turnover from 1998 to 2010 (BIS, 2010). Given the size of the market and the importance exchange rates have for a country`s economy, it is easy to see why it is important for economists to understand the dynamics of this market.

According to Williamson (2009), exchange rates are now considered to be the decisive link between the internal economy of a country and the international economy. He argues that given the small variations in price levels, the nominal exchange rate is the key determinant of the real exchange rate in the short and medium terms, and this again is a key determinant to determine economic stability and the incentive to engage in trade (Williamson, 2009). Furthermore, exchange rates also valuate the asset holdings for a country. Despite the clear importance, it has been difficult for economists to find a data coherent exchange rate model.

The first years after the breakdown of the Bretton Woods system saw some successful attempts of exchange rate modeling, like the Overshooting model of Dornbusch according to Rogoff (2009). This temporary pinnacle received a major blow with the publications of Meese and Rogoff`s now famous articles from 1983, where they showed that a random walk model could outperform structural exchange rate models in forecast competitions. These models were primarily based on fluctuations in various macroeconomic variables or “fundamentals” as they are called in the literature.

Ever since Meese and Rogoff`s dismissal of the classical exchange rate models, it has been a prioritized goal for economists to find a reliable model that could model exchange rates in a consistent way (Meese and Rogoff, 1983a 1983b). Despite the efforts and hundreds of studies, little progress was made during the two first decades after their articles according to Rogoff (2009). The standard macroeconomic models of exchange rates has shown to have little significant explanatory power on frequencies higher than semiannual, as described by Rime and Sojli (2006).

Jeffrey Frankel and Andrew Rose even concluded in an article published in the Handbook of International Economics back in 1995 that macroeconomic variables were relatively unsuitable for prediction of exchange rates; "*to repeat a central fact of life, there is remarkably little evidence that macroeconomic variables have consistent strong effects on floating exchange rates, except during extraordinary circumstances such as hyperinflations.*" The problem of finding good right-hand side variables in the regressions of exchange rates has been a mystery. It has been dubbed the "exchange rate disconnect puzzle" and has referred to as one of the six big puzzles in international macroeconomics according to Obstfeld and Rogoff (2000).

This failure have led researcher to try another approach in their quest of finding a model which can explain exchange rate movements. While the classical macroeconomic models dismiss agent heterogeneity and information advantages, microstructure highlights the act of trading and the notion that there exists private information which in turn can affect exchange rates. Order flow which is transaction volume that is signed (Lyons, 2001), works as an information aggregator and cause the exchange rate to move according to this theory.

Microstructure has especially proved to be successful for high frequent data, providing models which have been able to explain a large proportion of exchange rate movements at shorter horizons. Critics have however claimed that the price effect from order flow is transitory and not long lived. Killeen et al. (2006) showed that order flow is cointegrated with exchange rates implying that order flow do have persistent effects on exchange rates. Recent literature (Chinn and Moore, 2010) have also attempted to apply microstructure in order to explain exchange rate movements at longer horizons. This is an attempt to fill a hole which macroeconomic models have proved unable to explain.

This thesis is an extension to the work done at this level of frequency. I utilize two microstructure models in order to explain monthly exchange rate fluctuations for four major exchange rates. Building on theoretical foundations explained in Killeen et al. (2006), I choose to adjust the order flows in my thesis in an attempt to model the time varying price impact that order flow have during turbulent times. Furthermore cointegration tests are made in order to check if order flow has a persistent and long lived effect on exchange rates.

The thesis is organized in following manner; chapter 2 outlines two different approaches to exchange rate modeling, the classical way with macroeconomic "fundamentals" and the microstructure approach which highlights agents heterogeneity and information superiority. The role of order flow in this setting is explained and also why it is important determinant for explaining exchange rate fluctuations. Also included are some important facts about the foreign exchange market structure. Chapter 3 contains a brief, but intuitive explanation of the two models which are going to be used in this thesis, the Portfolio Shift model and the Liquidity Shock model. Chapter 4 gives a thorough description of the data series used in this thesis. An explanation of how I create order flow series is also provided. Furthermore, the times series properties for the dataset are tested for and discussed. Chapter 5 presents the results found in this thesis. Section 5.1 deals with econometric results[2] from the Portfolio Shift model with various sorts of proxies for order flow. Section 5.2 show results from Johansen cointegration testing for both the models. Vector Error Correction Models based on the Liquidity Shock model are also estimated for each of the exchange rates. Chapter 6 concludes and proposes some potential extensions to this thesis.

[2] Estimations and other econometric results in this thesis have been done with the statistical software EViews, version 7.1. More information about the software package can be found at www.eviews.com.

2 Different approaches to exchange rate modeling

Lyons (2001) describes the distinction between standard macroeconomic models and the microstructure models of exchange rates in a brief and concise way.

2.1 The macro approach

This approach has been the standard way of modeling exchange rates since the resolution of Bretton Woods in the 1970s. Trade flows and macroeconomic “fundamentals” are important variables for determining exchange rates in this approach. Investors and other market participants are thought of as rational people who look for the best place to invest their money. In order to invest in other countries, investors need to exchange their money. Information regarding expected payoff would therefore generate movements in exchange rates according to this approach. Variables of interest often include output growth, interest rates, inflation rates and money supply. These are all variables that can affect expected payoff for an investor.

According to Uncovered Interst Parity (UIP), news about higher deposit rates in Japan would lead to an immediate appreciation of the JPY against other currencies. Higher Japanese interest rates attract investors to invest more of their money in Japan because of higher expected return. This in turn would generate more demand after Japanese Yen since Yen is needed in order to invest in Japan. Increased demand after Yen should lead to an appreciation of Yen against other exchange rates. All this happens instantaneously and adjustment of prices takes place when the news is published. The appreciation is needed in order to make room for the following depreciation so that UIP holds. This mechanism is also known as “overshooting” and is a feature in the sticky-price monetary model associated with Dornbusch (1976).

In theory, no actual trading is needed in order to move prices. News about macroeconomic variables is assumed to be publicly available, so any new payoff relevant information is enough to move prices itself. Prices move sufficient to sustain an equilibrium where positions are willingly held. The prices of the assets considered are therefore effective in the sense that all relevant information are aggregated and given by the price of the asset. According to Lyons (2001), it is assumed that all information relevant for payoff is publicly known for all agents as well as the mapping from information to price. In such a setting, the act of trading is dismissed of having any relationship with the price setting, trading occur only if the dealers need to trade in goods or have liquidity needs as explained in Rime (2001).

The classical macroeconomic approach have struggled to find support for their models at biannual frequency and have struggled even more at higher frequencies as quarterly or monthly, according to Rime (2001). The huge trading volume present in exchange rate markets has proved to be a difficult feature to model. One of the assumptions which are common for these types of models is the one of homogenous market participants. Studies have however proved that there might be heterogeneity amongst market participants; see (Bjønnes et al. 2005; Bacchetta and Van Wincoop 2006). This suggests that models which incorporate agent heterogeneity could be more fruitful in explaining exchange rate movements. The microstructure approach which is described in next section is an attempt of this.

2.2 The microstructure approach

This approach to exchange rate has received a lot of attention since the start of the last decade. The microstructure approach has proved more fruitful than the classical macroeconomic models in explaining exchange rate movements, especially at higher frequencies. Rather than focusing on macro fundamentals, microstructure economists turn on the “microscope” and focus on topics such as asymmetric information and heterogeneous agents. The most famous paper is perhaps the article of Evans and Lyons from 2002. The authors showed that a microstructure model with microstructure variables could explain a huge portion of daily exchange rate movements for two exchange rates.

2.2.1 The importance of private information

As the name suggest, this approach rather focuses on microeconomic variables than macroeconomic variable. As Lyons (2001) describes, there are three crucial assumptions which are included in the standard macroeconomic exchange rate models, which are relaxed in microstructure literature.

1. Information: all participants have the same information and the mapping from news to price is also publicly known.

2. Participants: all participants are equal in the way the affect prices, size of the participants for example are an irrelevant factor.

3. Institutions: the way the participants act does not affect prices, trading mechanism are irrelevant for pricing, Lyons (2001).

The information assumption is an especially important point. Microstructure approach relaxes the assumption that all price relevant information are available for all agents, it is possible that some people know more than others. In addition, microstructure relaxes the assumption that the mapping from information to price is publicly known. Lyons (2001) and Sojli and Rime (2006) distinguishes between two types of private information based on if its payoff relevant information or if its discounting relevant information. Writing the exchange rate as a function of expected payoff and discounting factors;

$$S_t = \frac{E\{S_{t+1}(M_{t+1})|\psi_t\}}{1+R_t+\tau_t} \tag{1}$$

where S is the price of the asset, in this case the exchange rate. The exchange rate is hence a function of future macro-fundamentals M based on the available information set ψ. The discount factors consists of the interest rate R and risk premium τ.

Payoff relevant information is all information that can affect the payoff of the asset owner. For the foreign exchange market, payoffs often centers on interest rates and interest differentials between two countries. Private information in this case will therefore be information about the macro “fundamentals” M. The set of expected macro “fundamentals” M_{t+1} is based the available information set today ψ_t. Macroeconomic models assume that people who have the same information set also have the same expectations about the future. Microstructure theory opens up for the possibility that people could interpret news differently, so even if two agents have the same information set, they do not necessarily have the same view about the future. Two investors who see the same news could interpret them differently, and hence act in separate ways. Market participants are not homogenous and expectations could differ across participants (Rime and Sojli, 2006).

The other main type of private information is concerning the factors in the numerator of (1), the discount rate. Risk-averse agents require a risk premium to hold risky positions. If the risk increases, a risk-averse agent would require a lower buying price in order to be willing to hold the asset. In the exchange rate market, players often need to absorb transitory mismatches in supply and demand. Since risk is not evenly spread out between market participants and agents have different risk assessment, prices could be affected in the short run. Information about agent`s risk assessment and required risk premiums are therefore regarded as private information that could affect prices (Lyons, 2001).

2.2.2 Foreign exchange market structure

In order to understand the models used in microstructure, a proper understanding of the foreign exchange market features are needed. It is therefore worth to explain the features of the foreign exchange market structure before continuing. The foreign exchange market is often described as two-tier market with the retail market and the interbank market as the two tiers. In the retail market, banks trade with customers. In the interbank market, banks trade with each other. Non-bank customer orders represent the most important source of private information for banks (Lyons, 2001). As discussed above, these orders could stem from a variety of sources. While informative, these customer orders are not available to other than dealers working in the bank where the order is placed.

Dealers working at banks often trade directly with each other in the interbank market. In this market dealers trade frequently and often with pre-specified amounts of currency. Trading could stem from direct trades where a dealer calls up another dealer or indirect trades where dealers submit limit and market orders; hence each trade often has an initiator. Dealers only have information regarding the trades they participate in. Based on these features, dealers can observe it own order flow against other dealers at the end of the day. Interdealer trading is informative about the currency orders each dealer receives from customers, and by observing interdealer order flow, dealers can infer any private information from other banks customers.

Another notable feature in the foreign exchange market is that despite the huge trading volume, dealers often tend to have small or zero position at the end the day (Evans, 2011).

The Portfolio Shifts model in section 3.1 is an attempt to incorporate the mechanism of how customer orders for foreign exchange ultimately affect the price of currencies.

2.2.3 Order flow as information aggregator

As mentioned above, private information is important for the exchange rate according to microstructure theory. Private information results in trading since the information advantage give rise to gains from trade. We would therefore need a variable to aggregate private information amongst market participants. The literature often use order flow as the information aggregator.[3] Order flow according to Lyons (2001), is transaction volume that is signed. The sign is given according to what the initiator of the trade did. If the initiator of the trade sold the asset, we have a negative order flow for that asset. Similarly, if the initiator of the trade bought the asset, we get a positive order flow for that asset.

Take an example with two currency traders. If a trader (the initiator) wants to sell some euro (EUR) against US dollar (USD), he could call up a second trader (the passive part). The second trader is expected to quote prices he is willing to trade on and acts as a price-setter in this case. If the first trader accepts the bid price set by the second trader who, we would get a negative order flow for EUR against USD equivalent to the volume of the trade. Equivalently, we also get a positive order flow of the same amount for USD against EUR. These two are therefore opposite of each other. Order flow is therefore seen as an information aggregator which aggregates private information and differing expectations amongst market participants as mentioned above.

The action to the initiator of the transaction is important and separates order flow with the more common measure of net purchase. The net purchase is defined as bought amount of an asset minus sold amount of an asset and would in this case have been zero if we had summed the trades for these two traders, whereas the order flow are non-zero. Order flow has proved to be successful in describing exchange rate movements. It is also important to stress that it is only unexpected order flow that should move the price. Expected order flow which market players anticipate, should not be moving prices as they are already counted for. We have different methods of extracting unexpected order flows from the actual order flows. One

[3] Another variable used for this purpose in microstructure theory is the bid and ask spread, according to Lyons (2001).

option is to take the first difference of order flow, another filtering method is to take the residuals from an AR(p) regression. I will come back to this topic later in the thesis.

The inclusion of order flow does not mean that we have to exclude macroeconomic explanatory variables. It is a common view (Rime et al., 2010) that macroeconomic fundamentals are the cause of exchange rate movements, but that the proximate cause is order flow since it tells us how people interpret the information. Findings in Rime et al. (2010) suggest that macroeconomic variables are determinants of order flow, and order flow is therefore most easily seen as a transmitting mechanism for fundamentals. Different from those variables, order flow gives a real pointer for how people interpret fundamentals since order flow assumes that you actually put money on the table according to Lyons (2001). Macroeconomics variables are therefore still valid to use and they affect the exchange rate both directly but also indirectly through order flow (Rime et al., 2010). This view is often called a "hybrid view" according to Lyons (2001), the two other views is the standard macro view explained in section 2.1. The pure microstructure view only take use of microstructure variables and reject macroeconomic fundamentals. The different approaches and how they affect prices are illustrated in figure 1.

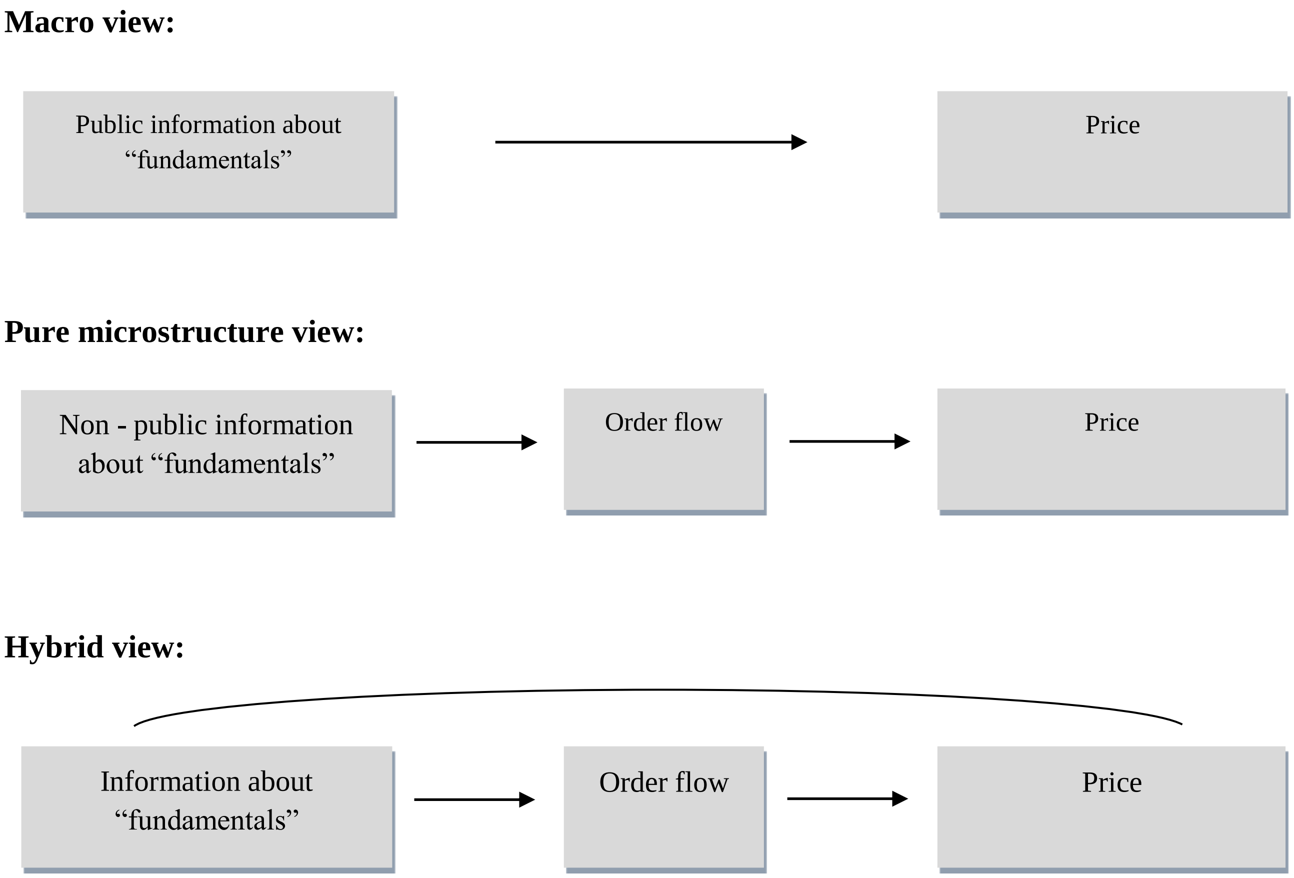


Figure 1: *Illustration of different approaches to exchange rate modeling*

Source: Lyons (2001)

3 Models

In this section I will go through the theoretical background for the models used later in this thesis. Section 3.1 describes the Portfolio Shift model used by Evans and Lyons (2002) and Killeen et al. (2006). The Liquidity Shock model, developed by Chinn and Moore (2010) are reviewed in section 3.2.

3.1 Portfolio Shift model

The intuition underlying this model is that there exists uncertain public demand for foreign exchange. These differences can arise either because agents have different views about the future expected cash flow (the numerator in asset valuation), or because of different information about market-clearing discount rates (the denominator in asset valuation). Cao et al. (2006) studied private information in the “numerator” while Evans and Lyons (2002) focused on the last type of differences. According to Evans and Lyons (2002), agents could have different views about the future state of economy for several reasons. The authors mention shocks to liquidity demand, shocks to hedging demand and time-varying risk as possible explanations. Rime and Sojli (2006) suggests that these differences also could stem from idiosyncratic risk assessment or risk compensation. A thorough explanation of this model can be found in both Lyons (2001), chapter 7.1. and Killeen et al. (2006). I will only go through the underlying intuition of the model without involving mathematical expressions.

Agents place orders according to their demands and create customer order flow for foreign exchange. These customer orders could contain private information of how the agents expect the economy to develop and are not observable for all foreign exchange dealers according to Cao et al. (2006). However, through the act of trading within the interdealer market, dealers can infer the aggregate customer order flow by observing interdealer order flow. The information these customer orders convey are aggregated in the trading process and order flow should therefore contain information about the aggregate public view about the future state of economy. Order flow can therefore be interpreted as a transmitting mechanism for macroeconomics explanatory variables that affects the price of currency.

The model specifies three rounds of trading, all happening intraday. The first round starts with a payoff which is observable for all. It is most natural to interpret this payoff as the change in short term interest rate differentials as stated in Killeen et al. (2006). After the payoff, non-bank customers update their belief about the future state of economy and rebalance their portfolios and demand foreign currency thereafter. Dealers quote prices and customers buy foreign exchange from the dealers. These customer orders represent portfolio shifts for the non-bank agents. The customer order flow created from this is not observable beyond counterparties involved.

The second round consists of trading amongst the dealers in the interdealer market. Reasons for this could be to share inventory risk and to get rid of unwanted positions, (Lyons 2001). Each dealer quotes prices that they are willing to trade on. These quotes are observable for all participants in the interdealer market. At the end of the second round, all agents learn the cumulated order flow from the period. Since dealers trading in this round are assumed to be proportional to their customer trades, dealers can infer the aggregate portfolio shift of the customers by observing interdealer order flow.

In the third round, dealers trade with agents again to share overnight risk. They set the prices so the public absorb excess currency and to get close to zero position at the end of the day. The total change in exchange rates through these three rounds is a function of order flow and payoff relevant information. The latter is simplified to be the difference in interest rates. Based on this theory, Evans and Lyons (2002) estimate regressions of the form

$$\Delta s_t = \beta_1(i_t - i_t^*) + \beta_2 of_t \tag{2}$$

where Δs_t is the change in log spot exchange rate, of_t is the order flow and $(i_t - i_t^*)$ is the nominal interest difference. They find that while the interest difference only can explain a small portion of the change in spot rate, order flow has significant explanation power on the exchange rate, raising adjusted R-squared from 1% to 64% for the Deutsche Mark/US dollar exchange rate. Figure 2 illustrates the timing of the model.

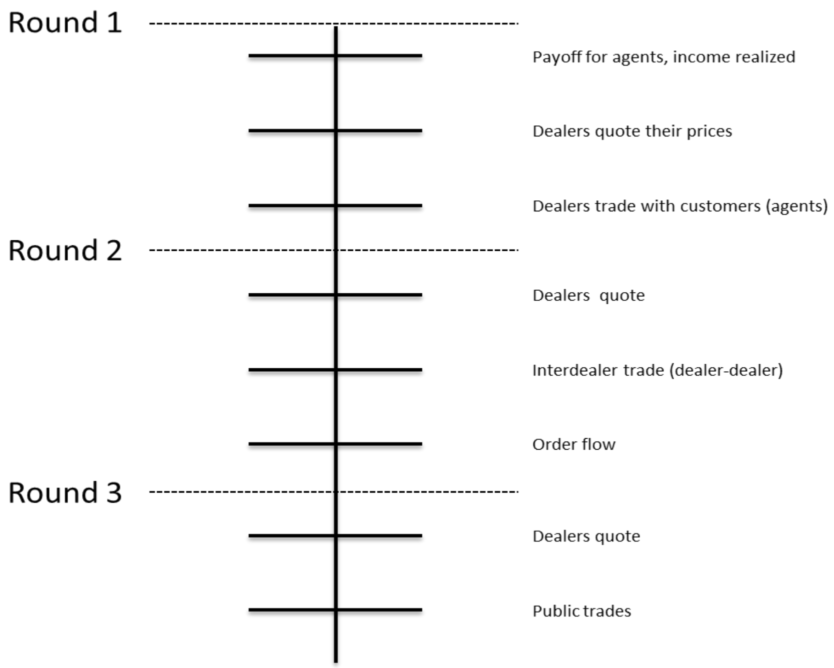


Figure 2: *Timing for the Portfolio Shift model*

Source: Killeen et al. (2006)

The Portfolio Shift model was originally developed to model intra-daily exchange rate fluctuations. Berger et al. (2008) argues that this model produces less impressive results than those obtained in Evans and Lyons (2002) when the data frequency gets lower. According to the authors, both R-squared and price impact parameter of order flow decreases when the data have lower frequency. Chinn and Moore (2010) estimate the regressions implied by the Portfolio Shift model at monthly frequency with their dataset and they find that order flow still manage to explain a sizeable proportion of monthly fluctuations in two exchange rates.

3.2 Liquidity Shock model

Chinn and Moore (2010) introduce a model which utilizes private liquidity preference shocks amongst agents to explain exchange rate movements. This idea builds on the assumption made in Evans and Lyons (2002) where they suggested that order flow could contain information about private liquidity shock. Hence Chinn and Moore argue that money demand is exposed for idiosyncratic shocks which follow a unit root process. Their paper starts out with an explicit assumption for the utility function of the agents, namely the constant elasticity of substitution (CES) utility function:

$$E_0 = \sum_{t=0}^{\infty} \delta^t \frac{\left[\left[C_t^j\right]^{\frac{\theta-1}{\theta}} + e^{\frac{\eta^j}{\theta}} \left[\frac{M_t^j}{P_t^j}\right]^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}}{\frac{\theta}{\theta-1}} \tag{3}$$

Subscript j= H, F for home and foreign respectively. C_t^j are consumption at time t. M_t^j is nominal money balance, P_t^j is the price of consumption, or price level. θ and δ are the CES-parameter and the discount rate respectively. Both of these two parameters are public information. The last parameter η is the preference parameter for money demand. Chinn and Moore assume that this parameter follows a unit root process.

$$\eta_t^j = \eta_{t-1}^j + \varepsilon_t^j \tag{4}$$

Expression (3) is maximized with respect to the budget constraint, and using the Purchasing Power Parity (PPP)[4], they derive the following relationship for determination of exchange rates[5], Chinn and Moore (2010):

$$s_t = [(m_t^H - m_t^F) - (c_t^H - c_t^F) + \theta(r_t^H - r_t^F)] - (\eta_t^H - \eta_t^F) \tag{5}$$

The terms in the square brackets are typical representation for the monetary models, while the last expression containing the private liquidity preference shock are given in brackets. Assuming that θ is small as Chinn and Moore does, the exchange rate should be explained by instability in money demand, or more precisely the difference in money demand. The values of η is unknown and the authors claim that it only can be revealed through the trading process and contained within the order flow. The mechanism linking money demand to order flow is similar to the one explained in the portfolio shift model. Agents experience private liquidity shock and demand currency from dealers thereafter. Dealers then trade amongst themselves in the interdealer market and order flow are available to all dealers at the end.

Killeen et al. (2006) found that Portfolio Shift model in the previous subsection also implied a cointegration relationship between cumulative order flow, interest differentials and exchange

[4] Lower letter case symbols represents the natural log of the corresponding variables and $r_t^j = \frac{i_t^j}{1+i_t^j}$

[5] The maximization and algebra manipulation are shown in appendix B.3

rate levels implying a long run relationship between order flow and exchange rates. The authors showed that order flow can explain a high proportion of exchange rate movements in the short run, and that the effects of order flow on exchange rates were persistent and long lived. Furthermore, adjustment to equilibrium occurs through exchange rate adjustment and not order flow adjustment as the error correction term only were significant in the exchange rate equation and not the order flow equation (Killeen et. al, 2006).

In similar fashion, Chinn and Moore argue for a cointegration relationship between cumulative order flow, traditional macro fundamentals and the level of exchange rate. The macroeconomic “fundamentals” consists of money supply, interest rate and consumption. Consumption is replaced by a measure for income, namely industrial production as stated in Chinn and Moore (2010). As order flow should contain shocks to demands for liquidity, cumulative order flow should therefore capture the cumulative liquidity demand as specified by equation (5). Exclusion of cumulative order flow in this model would lead to lack of cointegration due to misspecified model. The main difference between these two models econometrically is therefore the inclusion of macroeconomic fundamentals in the Liquidity Shock model.

4 Data

The dataset consists of monthly data for exchange rate positions, exchange rates, interest rates, money supply, consumer price indices and industrial production for five countries. Most of the series starts in January 1994 and ends in June 2010. The result is 198 monthly observations over a period of 17 years.

Attention is put on four exchange rates. I am going to study US dollars (USD) against Canadian dollars (CAD) and USD against British Sterling (GBP) as well as the more widely studied currency pairs of USD against Japanese Yen (JPY) and USD against Euro (EUR). These four currencies pairs are all amongst the biggest currency pairs measured by market turnover. USD/EUR is by the far biggest with a daily turnover of 1.1 trillion US dollars while USD/JPY and USD/GBP are ranked second and third respectively. USD/CAD is ranked fifth with a daily turnover of 182 billion US dollars. Together, they represent a total of 55% of the daily turnover in the foreign exchange market, according to BIS (2010). In this thesis, USD will be the home currency in which I measure foreign currency (CAD, EUR, GBP, JPY) against. The term foreign currency will therefore refer to the currencies of CAD, EUR GBP and JPY. Exchange rates are measured as amount of foreign currency needed to buy one USD, in other words the price of USD measured in foreign currency.

Exchange rate positions are gathered from the Office of Monetary and Financial Management. From these data, it is possible to create proxies of order flow series. The data are published quarterly in Treasury Bulletin and is released by Financial Management Service, a Bureau of the United States Department of the Treasury (TB, 2010). The raw data in this dataset consists of series with weekly frequency, and I have therefore aggregated these data as sum over month in order to get monthly data series.

Exchange rates and interest rates are downloaded from the Reuters Ecowin Pro Database. Both types of rates are date matched against the dates of the reported exchange rate positions. Consumer price indices, industrial production and money supply for the five countries of interest are downloaded from Bloomberg and have monthly frequency.

4.1 Exchange rate positions and net options

Exchange rate positions and net option positions are collected from the Treasury Bulletin which is published quarterly. The data series are originally weekly data on foreign currency holdings of large foreign participants in the exchange rate market according to Tranvåg (2009). The data on exchange rate positions contain series on purchased and sold spot contracts of foreign currency against USD for large foreign exchange market participants in the U.S. In addition to spot contracts, it also includes forward contracts bought and sold, futures bought and sold, and one half the notional amounts of foreign exchange options bought and sold according to TB (2010).

4.1.1 Creating order flows from exchange rate positions

I have transformed these weekly series into monthly series by adding up the weekly observations within each month.[6] All series are measured in units of foreign currency (CAD, EUR, GBP or JPY). For the data on euro, I have used the corresponding series for the Deutsche Mark (DEM) in the period up to January 1999. The DEM series are all divided by 1.99538 which is the official fixed exchange rate between Deutsche Mark and euro, given by the European Central Bank (ECB). For EUR, CAD and GBP, the series are in billions of respective currencies. For JPY, measurement is in trillions of yen.

By subtracting sold contracts from the bought contract of currencies, I can create series on net purchase of foreign currency. These series are a measure of net buying pressure in the market for foreign currency. As noted above, the microstructure literature stresses the importance of the action to the initiator of the transaction. It is the initiator`s action that gives rise to the sign in the order flow, if the initiator wants to sell foreign currency, the order flow for foreign currency will be negative even though the net purchase of foreign currency in this case would be zero when summing up the trading for these two parties. The dataset used in this thesis does however only contain information about sold and bought quantities of foreign currency and are silent about trade initiators. Hence I am not able to create order flows as defined in Lyons (2001).

[6] Since I do not have access to daily data, it has been impossible to get the exact amount of currency trade flows for each month, starting from the first day in the month and ending in the last. This might lead to somewhat imprecise measurement of the actual monthly series since the weekly observations not necessarily end at the last day of the month. Summing up weekly observations should nonetheless give a good approximation of the actual monthly currency trade flow.

The following example is illustrative for the distinction between order flow and net purchase. If the data show net purchase of for example GBP, it only means that the U.S. based market participants have bought more GBP than they have sold during the given time period. It does not however necessarily translate into a positive order flow for GBP, since it could have been that the U.S. based market participants who bought GBP were the passive parts in the trades. If the U.S. market participants were on the passive side, it would mean that the other part were the initiators of the trade. Since they wanted to sell GBP and buy USD and they were the initiators, this would translate into a negative order flow for GBP against USD even if our statistic suggested a positive net purchase of GBP.

The lack of information in my dataset regarding trade initiators does therefore require an assumption of how U.S. market participant's trade. If I assume that they are mainly on the initiating side of the trade, I could expect that a net purchase of foreign currency in the data would translate into positive order flow for foreign currency against USD. If I however assume that the U.S. based banks are taking positions as market-makers or price-setters, being the passive part in the trades, I could expect a net purchase of foreign currency in the dataset to translate into negative order flow for foreign currency against USD. The assumption I take is crucial for the sign in front of the order flow coefficient when estimating the models later. I therefore make the following assumption:

Assumption #1: U.S. based market participant's acts as price-takers, trading on foreign market participants quotes. Hence they are on the initiating side of the net of trades.

Assuming that they are initiating the net of trades and being the initiator of the "margin" trades that lead to either positive or negative net purchase, translate into an interpretation of position taking. As desired position taking also convey information, a positive net purchase after for example GBP can be interpreted in the way that investors believe GBP are underpriced and hence are willing to take positions in GBP. Empirical evidence as stated in Rime (2001) suggests that this assumption is more likely and that U.S. banks do primarily trade at other banks quotes, being the initiator of the net of trades.

Based on the discussion above and the assumption I added, a net purchase of foreign currency in the data will translate into a positive order flow for foreign currency. Consequently, the term order flow will also be used instead of net purchase even though order flow in this case does not match the strict definition of order flow given in Lyons (2001).

4.1.2 Order flow

Since the order flows are denominated in units of foreign currency, I expect to find a negative sign in front of the coefficient for order flow when I estimate the Portfolio Shift model. Positive order flow for foreign currency should result in appreciation of the foreign currency as documented in the literature (Evans and Lyons, 2002). Figure 3 plot the four order flow series.

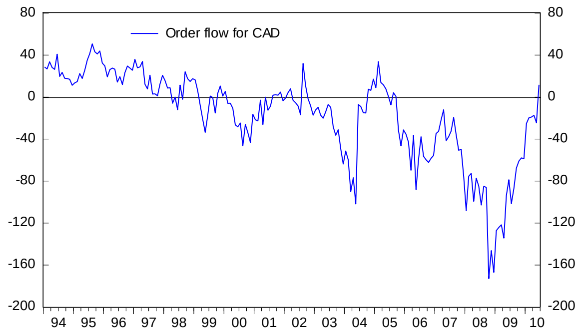


Figure 3 a: Order flow, CAD

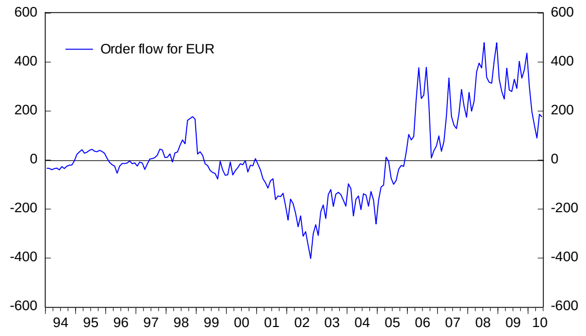


Figure 3 b: Order flow, EUR

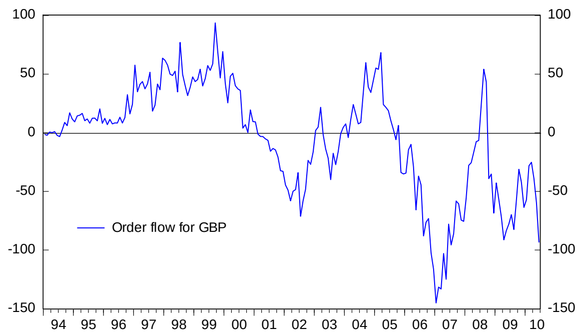


Figure 3 c: Order flow, GBP

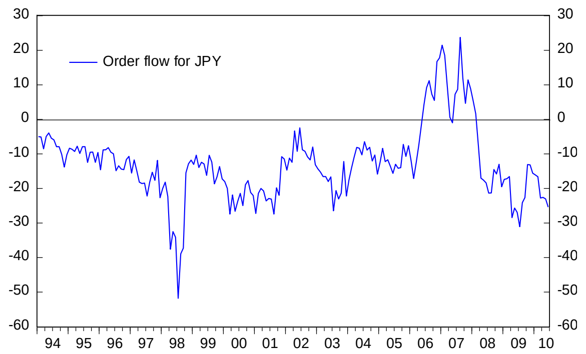


Figure 3 d: Order flow, JPY

Figure 3: *Order flow for four currencies against USD. Positive number indicates net purchase of foreign currency. Figure 3a, 3b and 3c are measured in billions of foreign currency; figure 3d is in trillions of JPY. January 1994 – June 2010.*

I also want to test the order flow series for non-stationarity.[7] Looking at the ADF test statistics for the order flows in table 1, I see that they are all lower in absolute value than the 5% critical Dickey-Fuller value. The 5% critical value for ADF test with an intercept and approximately 198 observations is -2.88 according to Hamilton (1994). This means that we

[7] Basic unit root theory and test methods are described in section B.1 in the appendix. A table with critical values for the ADF test is also provided.

cannot reject the null hypothesis of non-stationarity at this significance level. Since the test statistics for the differenced order flow series are all higher in absolute value than the critical Dickey-Fuller value, I conclude that the first difference in order flow is I(0) and that the level of order flow series is therefore I(1). Descriptive statistics for order flow series can be found in table A.1

Table 1: *ADF test results for order flows*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Level					
Order flow CAD	-2.2576	0.1870	1	14	196
Order flow EUR	-1.4753	0.5440	14	14	183
Order flow GBP	-2.1595	0.2220	6	14	191
Order flow JPY	-2.3267	0.1647	12	14	185
First difference					
Δ(Order flow CAD)	-18.6944	0.0000	0	14	196
Δ(Order flow EUR)	-3.2305	0.0198	13	14	183
Δ(Order flow GBP)	-15.7225	0.0000	0	14	196
Δ (Order flow JPY)	-5.6729	0.0000	9	14	187

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

4.1.3 Net option positions

In addition to the series on bought and sold contracts on foreign currency, there also exists series on net option positions for the same currency pairs considered above. The series indicates how U.S. based banks position themselves with options. The net option variable is an estimate of the relationship between an option`s value and an equivalent currency hedge. The net option positions are calculated as the options delta times the notional value of the option according to TB (2010). An option`s delta or hedge value is the change in the price of an option when the underlying asset changes.

The delta is simply the slope of the value curve of option evaluated at the current asset price according to Bodie et al. (2009). Since the notional value is positive, the delta will be the deciding factor for whether the net position is positive or negative. The delta could be positive and negative, depending on whether the option is a put or a call, or the position is long or short. A long call would for example have a positive delta, since the option value is increasing with the value of the underlying asset. Similarly, a long put would have negative delta.

Since the underlying asset is foreign currency, a long call for JPY would for example have positive delta, and hence result in a positive net option position for JPY. Likewise, a short call for Japanese Yen have negative delta and will result in a negative net option position for JPY. Monthly series of net option positions are created from weekly data in the same fashion as described above. The net option positions are measured in the same units as the order flows mentioned above. For CAD, EUR and GBP, the measurement is in billions of foreign currency while the net option series for JPY are in trillions of JPY. Figure 4 shows the net option variables for the four currencies considered against USD.

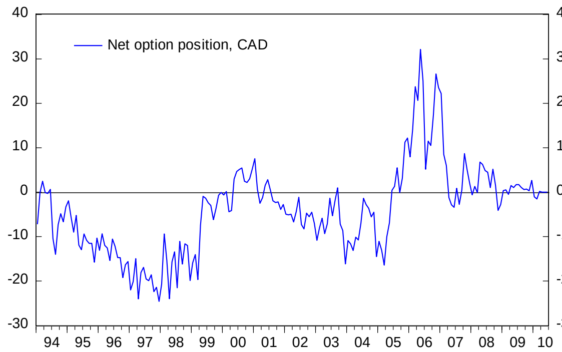


Figure 4 a: Net option position, CAD

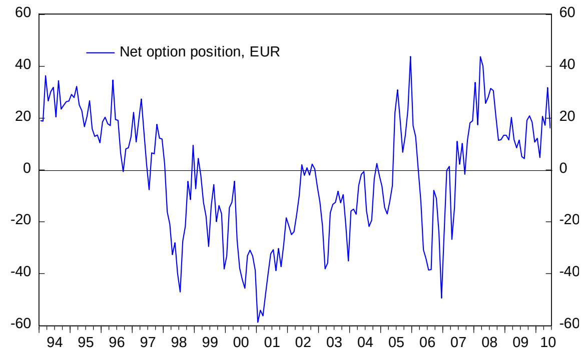


Figure 4 b: Net option position, EUR

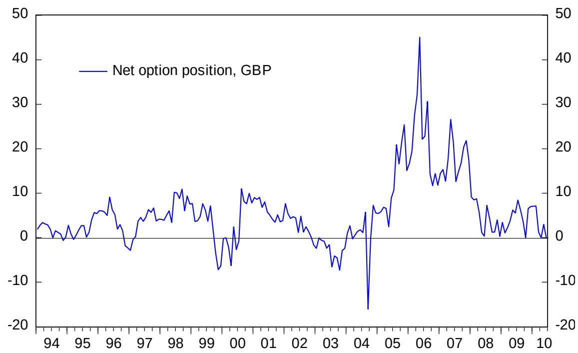


Figure 4 c: Net option position, GBP

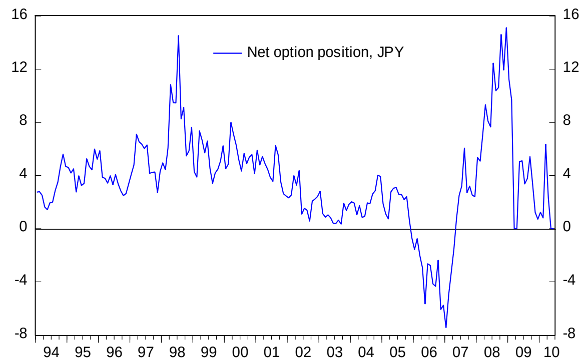


Figure 4 d: Net option position, JPY

Figure 4: *Net option positions for four currencies against USD. Positive number indicates positive net option position. Figure 4a, 4b and 4c are measured in billions of foreign currency; figure 4d is in trillions of JPY. January 1994 – June 2010.*

Looking at the properties of these series in table 2, I see that I am not able to dismiss the null hypothesis of non-stationarity for the series of CAD, EUR and GBP at 5% critical level since the critical value is -2.88 according to Hamilton (1994). The null is rejected for net option positions for Japan at 1% level.

Table 2: *ADF test results for net option positions*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Net option CAD	-2.1534	0.2243	11	14	186
Net option EUR	-2.3323	0.1630	14	14	183
Net option GBP	-2.6052	0.0937	9	14	188
Net option JPY	3.6212	0.0061	0	14	197

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

Options are widely used by traders to reduce their exposure in the market. If for example a trader has large positions in a certain asset and wants to secure himself against fall in the value of that asset, he could buy a put option on that asset. The value of a put option increase when the value of the asset decreases, so buying put options in this case will reduce the exposure for the trader. If options are mostly used for this purpose, we would expect the net option of each currency to exhibit negative correlation with the order flow. Buyers of foreign currency should also buy put options on the same currency in order to secure their positions according to this theory.

Table 3 shows that this interpretation is in line with the negative correlation coefficients I get for CAD, GBP and JPY. The positive correlation coefficient for EUR suggests that net option position in EUR follows the order flow. Interpretation of positive correlation could be that options for EUR are in a larger scale used for speculative measures. Options could be used to leveraging positions since the price of the options is lower than the price of the underlying asset (Bodie et al., 2009). Buying solely options without buying the underlying asset increases the risk. The potential reward is higher, but so is the downside. Descriptive statistics for net option positions can be found in table A.2.

Table 3: *Correlation coefficients between order flow and net option positions*

	Correlation coefficient
For CAD series	-0.5118
For EUR series	0.3186
For GBP series	-0.4088
For JPY series	-0.5626

4.2 Exchange rates

Exchange rates are collected from Reuters EcoWin Pro Database. The rates considered are end of day spot rates. The rates are matched against the dates of the exchange rates positions in order to get consistent data. The dataset consists of four different currencies measured against USD. Exchange rates are given by USD measured against the respective currency we are looking at, e.g. (USD/EUR) in the case of USD and EUR.

The rates will then tell us how much we need to pay for a USD in the respective currency we are looking at. Consequently, it means that the exchange rate will rise if USD appreciates as the price of USD denominated in currency will be higher. Similar to the exchange rate positions, I have used DEM in the period from January 1994 to December 1998 and transformed to EUR by using the fixed exchange rate between DEM and EUR given by the European Central Bank. The exchange rate series of USD/EUR is therefore a transformed series of the USD/DEM series for the period from 1994 to 1998. Figure A.1 in the appendix shows the four exchange rates. The series fluctuates a lot and the monthly standard deviations are ranging from 9.6% percent of its mean for USD/GBP to 15.3% of its mean for USD/EUR. High values of USD/CAD, USD/EUR and USD/GBP are reached in the first years of the new millennium before falling some. The graphs also show that the recent crisis in 2008 had an especially big effect on GBP who depreciated with more than 46% against USD in just over one year. Descriptive statistics for the four exchange rates are given in table A.3 in the appendix.

Results from the ADF test of the exchange rates in table 4 suggest that I cannot reject the null hypothesis since the test statistic is lower in absolute value than the 5% critical Dickey-Fuller value with an intercept included in the test and 198 observations (-2.88), indicating that the series are at least integrated of order one. Nominal exchange rates are often considered to be I(1) variables, so this result is not surprising.

Table 4: *ADF test results for the exchange rates*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
USD/CAD	-0.4978	0.8876	13	14	184
USD/EUR	-1.3377	0.6118	0	14	197
USD/GBP	-1.7608	0.3991	7	14	190
USD/JPY	-2.0360	0.2693	10	14	188

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

Since I will often use the change in log of the exchange rates as the dependent variable in this thesis, I choose to test these variables for non-stationarity as well. Results given in table 5 suggests that all change in log of exchange rates are I(0) variables as the test statistic is greater the 2.88 in absolute value which is the critical Dickey-Fuller value at 5% significance.

Table 5: *ADF test results for Δlog(exchange rates)*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Δlog(USD/CAD)	-4.5789	0.0002	12	14	184
Δlog(USD/EUR)	-13.1812	0.0000	0	14	196
Δlog(USD/GBP)	-6.1331	0.0000	6	14	190
Δlog(USD/JPY)	-7.6054	0.0000	3	14	193

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

4.3 Interest rates

As the case is with exchange rates, interest rates are also downloaded from the Reuters EcoWin Pro Database. I have also matched the dates of the interest rates with the dates from the exchange rate positions. The interest rates I consider are 3 month deposit rates.[8] From these interest rates, I create a variable called interest rate difference which is defined as the difference between the 3 month interest rates for the country I am considering and the U.S. Figure A.2 shows the four interest rate differential series.

From the graphs, it is easy to see that the 3 month interest rates in Japan have been lower than corresponding interest rate in the U.S. for almost the whole period. Comparing the four interest rate difference series, I see that they exhibit similar patterns. 3 month interest rate in the foreign countries was high compared to the U.S. in the beginning of our dataset. This difference gradually disappeared and fell below zero for three of the series until it reached a minimum in the first years of the new millennium (euro area, the UK and Japan). The differences rose again during mid 2000`s before slumping down around 2006. The financial

[8] I have also taken the difference between 12-month and 1-month deposit rates in order to create a variable that could proxy differences in inflation expectations. The difference between these two deposit rates measures the slope of the yield curve and could be interpreted as inflation expectation. Difference in inflation expectations could therefore be estimated by the difference in slope of the yield curve between two countries; $(i^*_{12M} - i^*_{1M}) - (i^{US}_{12M} - i^{US}_{1M})$. Including this variable into the Portfolio Shift model did not improve the fit of the model and hence further elaboration of this variable is skipped from this thesis.

crisis in 2007-2009 saw a rapid decrease of American interest rates compared to these countries before stabilizing around 0 for all four series at the end of our dataset. Descriptive statistics can be found in table A.3 in appendix A.1.

Looking at the Augmented Dickey-Fuller test statistics for the interest difference variables, I cannot reject non-stationarity in the case of the euro area and Japan. None of these two are significant at 5% significance level. For Great Britain, we have significance at the 5% level, while interest rate difference for Canada is significant even at the 1% level. Even though stationarity test indicates elements of I(0), I choose to treat these variables as I(1). Descriptive statistics for interest differentials can be found in table A.4.

Table 6: *ADF test results for the interest rate differences*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Interest diff CAD	-4.2015	0.0009	12	14	185
Interest diff EUR	-2.2157	0.2014	3	14	194
Interest diff GBP	-3.2542	0.0185	5	14	192
Interest diff JPY	-2.4147	0.1390	10	14	187

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

4.4 Other data

The rest of the series in the dataset are series on money supply, industrial production and consumer price indices for the five countries I am looking at. All these series have been downloaded from Bloomberg and have monthly frequency.

4.4.1 Money supply

I have used the M2 definition of money supply for all countries expect for the euro area where I have used the M2 equivalent M3 measure of money supply. All the series starts in January 1994 and ends in June 2010. I have normalized the data in order to be able to compare the money supply growth between countries. Normalization is done so that money supply in January 1994 starts at 100 for all countries. A graph with the normalized money supply for all five countries can be found in figure A.3.

I also create difference series between the foreign country of interest and the U.S., these are simply defined as the money supply in the foreign country of interest minus the money supply in the U.S. Since I am going to use these series in regressions later in this thesis, I choose to run ADF tests of the difference series directly.

Table 7 shows ADF tests for level, first change and second change of money supply differences. Level series seems non-stationary while first change series seems stationary for series on UK and Japan. Based on these test, money supply difference for the UK and Japan seems to be I(1), while money supply difference for Canada and the euro area looks like I(2) variable. It does contradict economic intuition that money supply difference have higher order of integration than I(1), so I conclude that I either have used wrong test specification or that the sample is not representative. I will treat money supply differences as I(1) in later econometric analyses even though the ADF test show some elements of I(2).

Table 7: *ADF test results for money supply differences*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Level					
Money diff CAD	-2.1893	0.2110	12	14	185
Money diff EUR	-2.2983	0.1737	12	14	185
Money diff GBP	0.4990	0.9863	14	14	183
Money diff JPY	0.3268	0.9781	13	14	184
First difference					
Δ(Money diff CAD)	-0.7227	0.8372	11	14	185
Δ(Money diff EUR)	-1.7304	0.4143	11	14	185
Δ(Money diff GBP)	-3.5654	0.0074	13	14	183
Δ(Money diff JPY)	-2.6465	0.0856	12	14	184
Second difference					
Δ^2(Money diff CAD)	-13.8471	0.0000	10	14	185
Δ^2 (Money diff EUR)	-10.6021	0.0000	10	14	185
Δ^2 (Money diff GBP)	-5.5550	0.0000	12	14	183
Δ^2 (Money diff JPY)	-5.8800	0.0000	14	14	181

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

4.4.2 Industrial production

Industrial production is a good estimate for Gross domestic product (GDP). Since GDP series only can be found at quarterly basis for most countries, I choose to use industrial production which is published on monthly basis. All industrial production series are seasonally adjusted. I have normalized the series of industrial production with the same method as with money supply series (displayed in figure A.4) and created difference series in the same fashion. As table 8 shows, industrial production difference series seems to be non-stationary while differencing them once makes them stationary. Hence I conclude that industrial production difference series can be taken as I(1) variables.

Table 8: *ADF test results for industrial production differences*

Series	Test statistic	P-value	Lag	Max lag	Observation in test equation
Level					
IPR diff CAD	0.0586	0.9617	3	14	194
IPR diff EUR	-2.2759	0.1809	1	14	196
IPR diff GBP	-1.6243	0.4682	9	14	188
IPR diff JPY	-2.1269	0.2344	10	14	187
First difference					
Δ(IPR diff CAD)	-5.9052	0.0000	2	14	194
Δ(IPR diff EUR)	-19.6299	0.0000	0	14	196
Δ(IPR diff GBP)	-3.5065	0.0088	8	14	188
Δ(IPR diff JPY)	-4.9344	0.0000	9	14	187

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

4.4.3 Consumer prices

Series on consumer price indices (CPI) starts in January 1994 for all countries expect for the euro area where the CPI series starts in January 1996. Hence normalization is set so that CPI starts at 100 in January 1996 for all five countries; the series are displayed in figure A.5. Differential series are created in the way as with money supply. ADF test results in table 9 suggest that consumer price differentials are non-stationary. Differencing them once, makes them stationary as the test results show, and I therefore treat them as I(1) variables.

Table 9: *ADF test results for consumer price index (CPI) differences*

Series	Test statistic	P-value	Lag	Max lag	Observation in test equation
Level					
CPI diff CAD	-0.5770	0.8714	13	14	184
CPI diff EUR	-0.8040	0.8150	13	13	160
CPI diff GBP	-0.1928	0.9358	13	14	184
CPI diff JPY	0.3584	0.9807	12	14	185
First difference					
Δ(CPI diff CAD)	-4.4042	0.0004	12	14	184
Δ(CPI diff EUR)	-4.7145	0.0001	12	13	160
Δ(CPI diff GBP)	-2.8382	0.0550	12	14	184
Δ(CPI diff JPY)	-3.5327	0.0082	11	14	185

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

5 Empirical results

In this section I present the empirical results I have obtained when I estimated the models presented in section 4. Section 5.1 deals with the estimation results from the Portfolio Shift model. The results I get from running this model on my data supports the validness of including order flow in exchange rate regressions, even at this level of frequency. As the regressions shows, order flow has a significant explanatory power at monthly frequency as well, when they are adjusted for uncertainty and price disagreement. I do also find that controlling for option positions improve the fit of the model.

In section 5.2 I test both model specifications for cointegration. Using the Johansen test and estimating VECM`s based on the test results, I find cointegrating relationships between the exchange rate, order flow and macroeconomic fundamentals for all four exchange rates.

5.1 Empirical results for the Portfolio Shift model

Chinn and Moore estimated regressions based on the Portfolio Shift model in their paper from 2010, including a constant into the regressions:

$$\Delta s_t = \beta_0 + \beta_1 interest\ diff_t + \beta_2 order\ flow_t + \epsilon_t \tag{6}$$

where $\Delta s_t$is the change in log spot rate, of_t is the contemporaneous unexpected order flow, $i_t^* - i_t$ is the interest rate difference. β_2 is often called the price impact parameter of order flow, in this setting it measures percentage change in the exchange rate caused by order flow. In order for equation (6) to be "balanced", it is necessary that all the variables included are I(0). Interest differentials in my dataset show some signs of non-stationarity, which may lead to an "unbalanced" test equation. I will nonetheless include interest differentials in level series when estimating, as is common in the literature.

Running the regressions implied by the Portfolio Shift model, I would expect to get negative coefficients in front of the interest difference variables as well as the order flow variables. Positive unexpected order flow should according to microstructure theory cause the foreign currency to appreciate. Since exchange rates are denominated in foreign currency, we would therefore expect the rates to fall. Chinn and Moore estimated the same regressions for their dataset stretching from 1999 and up to 2007 for the exchange rates of USD/EUR and USD/JPY. Their findings suggested that the Portfolio Shift model has explanatory power with monthly frequency as well. In their data, order flow variables are significant, correctly signed and inclusion of order flow in the regressions increased the adjusted R-squared considerably (Chinn and Moore, 2010).

5.1.1 Portfolio Shift model with unadjusted order flow

I estimate four regressions for each exchange rate, with the same specifications as in Chinn and Moore (2010). They are numbered [1] – [4] in table 10. The dependent variable in all four regressions is the change in log spot exchange rate. The ADF test statistic in table 5 showed that the variables are I(0) and therefore can be included in OLS regressions. This transformation of the exchange rate also enables me to interpret the coefficients of the independent variables in an easy way, namely as percentage change in the exchange rate caused by one unit change in the independent variables.

Model [1]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 interest\ diff_t + \epsilon_t$

For model [1] I have included a constant and an interest difference between the respective country and the US. Table 6 suggested that I could not reject the null of non-stationarity for series on Japan and the euro area, so caution is taken when interpreting the results for this model.[9] The model specification is not valid according to the microstructure theory and the Portfolio Shift model, as it does not include an order flow variable, but is illustrative for the explanatory power for macroeconomic "fundamentals".

Model [2]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 unexpected\ order\ flow_t + \epsilon_t$

In regression [2], I exclude the interest difference variable and include order flow to see if order flow can explain more of the variation in spot rate than interest difference can. As only unexpected order flows have price impact, I need to find a way to create unexpected order flows. One way is to take the change in order flow series and use this as unexpected order

[9] Augmented Dickey-Fuller test showed that some of the interest difference series in section 5.3 were integrated of order 1, so by including this variable into the Portfolio Shift model, I need to be careful with inference about model fit. As the results will show, interest differentials have little or no predictive power for the exchange rates I consider.

flow. The first difference of order flow series can be interpreted as unexpected order flow under adaptive expectations.

$$unexpected\ order\ flow_t = \Delta(order\ flow)_t$$

Differencing the order flow series also enables me to include it directly into the OLS regression since it now is an I(0) variable as suggested by the ADF test statistics in table 1. This model specification is not valid according to the Portfolio Shift model as it does not include a variable of public information. It is however interesting in the sense that it gives a taste of the explanatory power of order flow.

Model [3]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 interest\ diff_t + \beta_2 unexpected\ order\ flow_t + \epsilon_t$

Regression [3] is with both interest difference as in regression [1] and with unexpected order flow as in regression [2]. This model specification is valid accord to the Portfolio Shift model, but I need to be careful with inference as interest differentials seem to be non-stationary in my dataset.

Model [4]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 \Delta(interest\ diff)_t + \beta_2 unexpected\ order\ flow_t + \epsilon_t$

Model [4] is estimated with unexpected order flow as in regression [2] and [3] in addition to the change in interest rate differential. By taking the change in interest differentials, I can interpret the variables as unexpected interest differences and it also solves the non-stationarity problem as the first difference of interest differentials are I(0) variables as shown in table 6.

Since regression diagnostics in table C.3 suggest that the residuals exhibit heteroskedasticity, I choose to correct for any heteroskedasticity and/or autocorrelation by using heteroskedasticity- and autocorrelation consistent (HAC) estimators of the coefficient variances in all regressions (Newey and West, 1987).[10] In this way, I am able to get reliable t-tests for the coefficients. Furthermore, all the coefficients and standard errors are also scaled with 100 in order to reader-friendly. The interpretation of the coefficients now translates into

[10] I choose the Akaike Information Criterion (AIC) as the automatic lag length selector and automatic Newey-West bandwith when estimating the coefficient variance.

percentage point change in the exchange rate. The estimation outputs with my dataset are given in table 10.

Table 10: *Portfolio Shift model estimation output, model [1] – [4]*

Regressor	Dependent variable: Δlog(USD/CAD)				Dependent variable: Δlog(USD/EUR)			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
$Constant$	-0.1161 (0.1793)	-0.1088 (0.1695)	-0.1186 (0.1730)	-0.1081 (0.1616)	-0.1524 (0.2395)	-0.0400 (0.2165)	-0.1453 (0.2237)	-0.0498 (0.2340)
$Interest\ diff$	-0.0859 (0.1354)		-0.0887 (0.1323)		-0.2677 (0.1695)		-0.2707 (0.1654)	
$Unexpected\ order\ flow$		-0.0252 (0.0214)	-0.0253 (0.0215)	-0.0242 (0.0196)		-0.0077** (0.0034)	-0.0078** (0.0034)	-0.0075** (0.0037)
$\Delta(Interest\ diff)$				0.3523 (0.3867)				-0.5819 (0.7688)
Diagnostics								
Adjusted R2	-0.0036	0.0302	0.0268	0.0278	0.0107	0.0192	0.0304	0.0174
Observations	197	197	197	197	197	197	197	197

Regressor	Dependent variable: Δlog(USD/GBP)				Dependent variable: Δlog(USD/JPY)			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
$Constant$	0.0050 (0.2346)	-0.0005 (0.1938)	0.0029 (0.2174)	-0.0108 (0.1894)	-0.8870** (0.3780)	-0.1218 (0.2202)	-0.9341** (0.3733)	-0.1196 (0.2279)
$Interest\ diff$	-0.0045 (0.1936)		-0.0030 (0.1991)		-0.2222** (0.1063)		-0.2326** (0.1030)	
$Unexpected\ order\ flow$		-0.0009 (0.0175)	-0.0009 (0.0178)	-0.0030 (0.0176)		-0.1009* (0.0535)	-0.1041* (0.0554)	-0.1141** (0.0556)
$\Delta(Interest\ diff)$				-0.8607* (0.5010)				-1.4413 (0.9710)
Diagnostics								
Adjusted R2	-0.0051	-0.0051	-0.0103	0.0036	0.0115	0.0193	0.0326	0.0343
Observations	197	197	197	197	197	197	197	197

Notes: All estimated coefficients and standard errors are multiplied with 100. HAC standard errors are given in brackets. Estimation sample: January 1994 – June 2010.
***, **, * indicates significance at 1% level, 5% level and 10% level

As shown in the table, the results are quite disappointing. Despite that all the coefficients for interest rate difference and order flows are correctly signed, neither of them seems to have too much explanatory power for exchange rate movements.

Model [1] seems to have the worst fit of the four models in explaining exchange rate movements. Adjusted R-squared ranges from negative numbers to a max at 1.1% for the JPY. The interest difference are not significant at any of the levels we are looking at expect for the JPY regression where it is significant at 5% level. The conclusion, looking at model [1] is that a model with only interest difference included seems to be unsuitable for explaining exchange rate movements.

Model [2] where only unexpected order flow is included does seem to improve the fit somewhat. All adjusted R-squared are either higher or the same compared to model [1]. Furthermore, t tests suggest that order flow are significant for two exchange rates, namely for EUR (10% level) and for the JPY (5% level). For GBP and CAD, I am not able to dismiss the null hypothesis that order flow coefficients are zero. Even though the results are better than model [1], it is not satisfying with such low adjusted R-squared values as well as the fact that unexpected order flow does not seem to be significant across exchange rates.

Turning attention to model [3], I see that addition of the interest difference and the order flow does not yield any miraculous improvement of the results. Best fit for this regression is achieved for the models of EUR and JPY. Including interest rate into the regression does not change the coefficients of order flow too much signaling that the correlation between these two variables are relatively small. Furthermore, order flow variables are still significant in the regressions of JPY and EUR.

Using the change in interest rate difference instead of the levels in model [4] improves the fit in the case of GBP. Change in interest rate difference is also significant at 10% level. Including change in interest differentials in the other exchange rate regressions does not yield huge improvements in fit. In the regression for CAD, the new variable enters with a positive coefficients, which is opposite of what theory predicts. A interesting point I get from the results for this model is that the coefficient of unexpected interest rate differentials, expect for Canadian Dollar, are multiple times larger than interest rate differentials. This suggests that unexpected interest rate movements cause bigger fluctuations in the exchange rate than interest rate differentials in levels.

Summing up the results for these models, it seems that the variables included in the regressions are not able to explain exchange rate movements for the four exchange rates I am looking at. Moreover, unexpected order flow, here defined by change in actual order flow, does not seem to have the dramatic improvement on model fit as Chinn and Moore documented in their paper from 2010. Even though the coefficients are correctly signed, the variables are not systematically statically significant across exchange rates. While order flow seems to be a significant variable for one exchange rate, it can turn up to be insignificant for others. In addition adjusted R-squared are low, reaching a maximum at 3.4% in model [4] for the Japanese Yen equation.

5.1.2 Portfolio Shift model with adjusted order flow

Using the change in actual order flow as an estimate for unexpected order flow did not work very well. Another way to find unexpected movements in data series is to look at the residuals from regressions. More specifically, I can use the residuals from an AR(p) process as unexpected order flow.[11]

$$order\ flow_t = \beta_0 + \sum_{i=1}^{p} \beta_i order\ flow_{t-i} + \epsilon_t$$

The residuals from the autoregressive equation are hence thought of as unexpected order flow.

$$unexpected\ order\ flow_t = \widehat{\epsilon_t}$$

The number of lags included in the autoregressive equation can be decided by an information criterion, for example AIC or BIC and the maximum number of lag allowed is set to some maximum lag selector. Den Haan and Levin (1998) suggested that the maximum numbers of lags included in a whitening-processes should be the integer of $p_{max} = T^{1/3}$. Using this maximum lag selector, I get a maximum lag of 5 for the order flow series. I also choose the Akaike Information Criterion (AIC) as the choice of information criterion.

[11] This process of extracting the residuals from an AR(p) is called “pre-whitening” in EViews, and routines for “pre-whitening” are included in the software package.

Uncertainty adjustment by spot range

One would expect order flow to be more informative when market uncertainty is high, as the information they convey are of greater value in uncertain times. It also means that the price impact parameter is dependent on market conditions, order flow have larger price impact during uncertain times. This idea is embedded in the Portfolio Shift model and addressed in Killeen et al. (2006). In their article, they proved that the price impact order flow has on exchange rates is an increasing function of the standard deviation of the spot exchange rate.[12] The article is written in the context of regime shifts between fixed and floating exchange rates, but the idea that the price impact of order flow is increasing with market turbulence should be applicable in other contexts as well. Higher variability in the spot rate means a larger price impact of order flow according to Killeen et al. (2006). According to this proposition, order flow coefficient is contingent on market uncertainty and the connection between order flow and price is time varying. By adjusting for market uncertainty, it is possible to control for this variability explicitly.

There are other measures than standard deviation of spot rate that can be used to measure market uncertainty. The difference between the highest and lowest value of the spot exchange rate is a similar measure to the one of standard deviation, I will call this measure for spot range. A higher gap between the highest and the lowest spot value reflects higher variability in the spot exchange rate as a high standard deviation also does. As the order flow series originally have weekly frequency, I choose to define the monthly spot range as the average of the weekly spot range values within each month. Graphs of spot range are displayed in figure A.6 in the appendix. As seen by the graph, all spot ranges peaked during financial crisis in 2008 and 2009.

If order flows during uncertain times really convey more information than order flow during calm times, the proportion of variation in spot range explained by order flow should also be an increasing function of spot range. The R-squared in the exchange rate regressions should therefore increase with uncertainty measured by spot range. In order to formally show the

[12] The authors find that the price impact parameter of order flow in the Portfolio Shift model is defined as

$$\beta = 2\left[\left(\frac{1}{\theta(1-p^2)\sigma^2}+\frac{2}{\theta\sigma^2}\right)+\sqrt{\left(\left(\frac{2}{\theta\sigma^2}\right)^2+\frac{1}{(\theta(1-p)^2\sigma^2)^2}\right)}\right]^{-1}$$

Where σ^2 is the observed variance during a time period, θ is the absolute risk aversion parameter in an exponential utility function, and p is the probability that a floating exchange regime becomes fixed regime.

connection between exchange rate variability and information embedded in order flow I choose to perform rolling regressions of the portfolio shift model and compare the R-squared from these regressions with the spot range for each of the exchange rates.

The model which I use to perform rolling regressions[13] on is identical to model [2][14], except that unexpected order flows are now created from a "pre-whitening" process as described earlier. The R-squared from these regressions can be interpreted as proportion of variation in spot rates that unadjusted order flow manage to explain. As my datasets ends in 2010, I am able to study the effect of the financial crisis in 2008 and 2009. According to the theory described above, order flow during this stressful period is more informative than other periods and should accordingly manage to explain a bigger proportion of exchange rate movements leading to a higher R-squared for my rolling regression model.

Figure 5 displays the results. For USD/CAD, USD/EUR and USD/GBP I have started the sample in 2002 to focus on the effect of the financial crisis in 2008 and 2009. As for USD/JPY, the sample is adjusted to incorporate the Asian Crisis in 1997-1999. The results largely confirm the prediction made above. For USD/CAD and USD/EUR, the proportion of variation in spot exchange rate explained is rising with spot range during the financial crisis in 2008 and 2009. While the order flow are quite uninformative during periods of low spot range values, it becomes very informative during stressful times. As for USD/JPY, the graph show the same nice correspondence between R-squared and spot range, and R-squared peaks during both crisis in the sample. The picture is however less clear for the case of USD/GBP, but uncertainty adjustment seems to be valid for my dataset so I choose to adjust order flow for uncertainty[15].

[13] Rolling regressions are performed with a window of 36 months and one month steps.

[14] The model specified for rolling regressions:

$$\Delta \log(exchange\ rate) = \beta_0 + \beta_1 unexpected\ order\ flow + \epsilon_t.$$

[15] I have also checked the betas or the price impact coefficients in these rolling regressions against the spot range. The price impact becomes larger (more negative) during periods of relative high spot range values, which is in line with the theory that order flow convey more information during stressful times and that the price impact hence is larger as well. All correlations coefficients between spot range and order flow coefficients from these rolling regressions are negative.

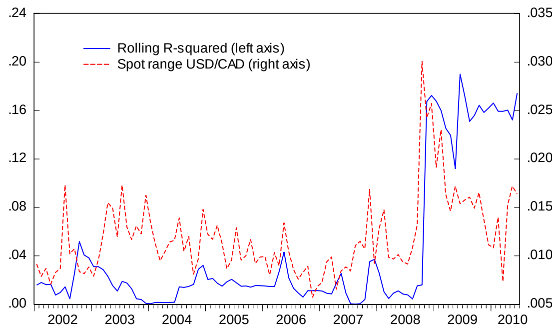


Figure 5 a: Spot range USD/CAD

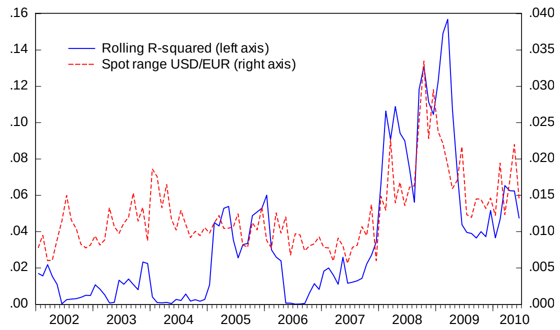


Figure 5 b: Spot range USD/EUR

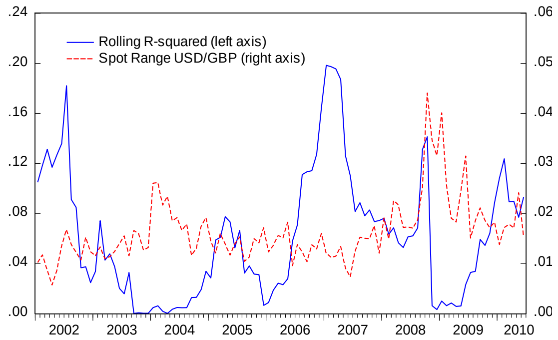


Figure 5 c: Spot range USD/GBP

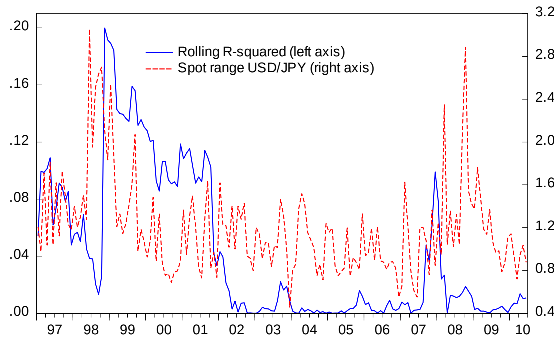


Figure 5 d: Spot range USD/JPY

Figure 5: *Comparison of R-squared from rolling regressions with spot range. January 2002 – June 2010 for graph 5a-5c and January 1997- June 2010 for graph 5d.*

The weighting for uncertainty is done by taking the monthly value for the spot range and divide that with the average over the whole sample.

$$\vartheta_t = \frac{spot\ range_t}{\frac{1}{T}\sum_{i=0}^{T} spot\ range_i}$$

The intuition behind this weighting is; a periodic value of spot range higher than the average indicates an uncertain market and the contemporaneous order flow should therefore be weighted upwards to take account for the higher price impact that order flow have in turbulent times according to Killeen et al. (2006). Notice that this adjustment does not change the sign of order flow.

Price disagreement adjustment by volume

I also choose to adjust the order flow for price disagreement in the market. Price disagreement in the market is indicated by higher market volume since higher trading volume means that people are more uncertain about the correct price to set. As stated in Berger et al. (2008), it is a common view amongst traders that larger trade volume corresponds with more informative order flow.[16] Higher market volume can indicate a high degree of price disagreement and economic intuition says that order flow during times of higher price disagreement are more informative than order flow when people agree about the price, and hence have a larger price impact. I therefore choose to give more weight to order flow when there is relatively high trade volume compared to order flow during low trade volume. The weighting is given according to volume over the average of the volume during the whole period. This does not change the sign of order flow either.

$$\omega_t = \frac{1 + volume_t}{\frac{1}{T}\sum_{i=0}^{T}(1 + volume_i)}$$

Based on discussion above, I create a variable called adjusted order flow. Adjusted order flow is a function of both the spot range and the trading volume.

$$adj\ (unexpected)\ order\ flow_t = unexpected\ order\ flow_t * \vartheta_t * \omega_t$$

Testing for non-stationarity, I find that the null of non-stationarity can be rejected for all adjusted order flow variables at 5% level. The test statistic from Augmented Dickey-Fuller tests translate into p-values ranging from 0.0000 to 0.0444 as shown in table 11.

Table 11: *ADF test results for adjusted order flows*

Series	Test statistic	P-value	Lag	Max lag	Observation in test equation
Adj. order flow CAD	-3.5576	0.0076	14	14	181
Adj. order flow EUR	-2.9253	0.0444	11	14	183
Adj. order flow GBP	-9.1730	0.0000	2	14	193
Adj. order flow JPY	-14.2467	0.0000	9	14	192

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

Since the ADF tests suggest that adjusted order flows are integrated of order zero, I am able to include them directly into the regression equation without taking any differences. The

[16] Berger et al. (2008) does not however share this view and argues for the opposite. According to the authors, lower trading volume corresponds with more informative order flow as low volumes signalize an illiquid market. They show this by comparing price impact coefficients of order flow from rolling regressions with trading volume. Similar conclusions are found in Payne (2003).

stationarity of the adjusted order flow series is caused by the “pre-whitening” process described above. The models are the same as before, except that adjusted order flow has replaced the change in order flow. I choose to re-estimate the regressions [2]-[4] with the adjusted order flow in order to see if the Portfolio Shift model fits better. Models are labeled [2-2] to [4-2]. The re-estimated results are given in table 12.

Table 12: *Portfolio Shift model estimation output, model [2-2] – [4-2]*

Regressor	Dependent variable: Δlog(USD/CAD)			Dependent variable: Δlog(USD/EUR)		
	[2-2]	[3-2]	[4-2]	[2-2]	[3-2]	[4-2]
$Constant$	-0.1868 (0.1455)	-0.2003 (0.1454)	-0.1867 (0.1406)	0.0047 (0.2252)	-0.0989 (0.2676)	-0.0042 (0.2153)
$Interest\ diff$		-0.1186 (0.1257)			-0.2468 (0.1903)	
$Adj. order\ flow$	-0.0193*** (0.0052)	-0.0194*** (0.0052)	-0.0193*** (0.0050)	-0.0052** (0.0026)	-0.0051** (0.0024)	-0.0051* (0.0030)
$\Delta(Interest\ diff)$			0.0214 (0.4861)			-0.6654 (0.5523)
Diagnostics						
Adjusted R2	0.1768	0.1754	0.1725	0.0333	0.0413	0.0325
Observations	196	196	196	195	195	195

Regressor	Dependent variable: Δlog(USD/GBP)			Dependent variable: Δlog(USD/JPY)		
	[2-2]	[3-2]	[4-2]	[2-2]	[3-2]	[4-2]
$Constant$	-0.0504 (0.1843)	-0.0532 (0.2529)	-0.0712 (0.1670)	-0.1014 (0.2268)	-0.9472*** (0.3260)	-0.0875 (0.2356)
$Interest\ diff$		0.0025 (0.1786)			-0.2398** (0.0945)	
$Adj. order\ flow$	-0.0124*** (0.0045)	-0.0124*** (0.0044)	-0.0152*** (0.0053)	-0.0788* (0.0455)	-0.0841* (0.0431)	-0.0917** (0.0400)
$\Delta(Interest\ diff)$			-1.4434*** (0.3736)			-1.7034 (1.0424)
Diagnostics						
Adjusted R2	0.0571	0.0522	0.0882	0.0292	0.0434	0.0514
Observations	196	196	196	193	193	193

Notes: All estimated coefficients and standard errors are multiplied with 100. HAC standard errors are given in brackets. Estimation sample: January 1994 – June 2010.
***, **, * indicates significance at 1% level, 5% level and 10% level

Looking at model [2-2] I observe that all the order flow variables are correctly signed and significant at a least 10% level. Adjusted order flow is significant even at 1% level for the case of CAD and GBP while adjusted order flow for EUR is significant at 5% level. Comparing equation [2] with [2-2] we see that adjusted R-squared is strictly higher for all four exchange rates. The best improvement is found in the regression for CAD. Adjusted order flow can itself explain almost 20% of the exchange movements during this 17 year period which is an increase from model [2] of 14%. The result for GBP is also encouraging, going from a negative adjusted R-squared to 6%. Coefficient estimates for order flow variables are not dramatically changed from model [2] to [2-2] expect in the case of GBP.

Model [3-2] with interest differentials included is not able to improve the model fit compared to model [2-2]. Adjusted R-squared increases with one percentage point in the JPY and EUR regressions compared to model [2-2] while it falls for the two other regressions. All interest rate differentials are insignificant expect in the JPY case, for GBP it is also wrong signed. Inclusion of interest differentials does not alter the significance of the adjusted order flow variables which stays significant and correctly signed for all exchange rates.

Model [4-2] is with change in interest differentials included. Comparing model [4-2] with model [2-2] I see that change in interest differentials have almost no explanatory power for the exchange rates of USD/CAD and USD/EUR. For USD/JPY and USD/GBP, it does add explanatory power increasing the adjusted R-squared to respectively 5 percent and 9 percent. Change in interest differentials is significant and correctly signed at 1% level for the GBP regression. Significance of adjusted order flow variables are virtually unaffected by including change in interest differentials and all are at significant at a least 10% level.

Summing up the results for the models with adjusted order flow, I find that adjusted order flow is correctly signed in all models for all exchange rates at a least 10% significance level. This is in great contrast to the results obtained with unadjusted order flow. Adjusting for uncertainty and price disagreement, I manage to highlight the price effect order flow have in turbulent times. Moreover, adjusting for uncertainty is theory consistent with the foundations of the Portfolio Shift model as it is presented in Killeen et al. (2006). The adjustment yield especially good results for the exchange rate of USD/CAD, with order flow significant at 1% level and explaining approximately 18% of the exchange rate fluctuation. The improvement in model fit from table 10 to table 12 for USD/CAD, and for the other exchange rates are in line with the findings from figure 5. Furthermore, it confirms the importance of adjusting order flow for uncertainty and price disagreement.

I also find as documented in literature (Evans and Lyons, 2002) that neither the price impact coefficient nor the significance of the adjusted order flow variables are much affected by including macroeconomic fundamentals (interest differentials or change in interest differentials). Macroeconomic fundamentals are unable to explain exchange rate fluctuations with a notable exception in the model [4-2] for the case of GBP. The price impact caused by adjusted order flow ranges from 0.5 basis points for the case of EUR, and up to 9 basis points in the case of JPY which is slightly lower than estimates found in Chinn and Moore (2010) for this model.

Based on analysis above, I draw following conclusion: following theoretical foundations established in Killeen et al. (2006) and modeling the order flow accordingly, I manage to get better results for the Portfolio Shift model. Adjusting order flow for uncertainty and market volume (price disagreement) improves the fit of the models and order flow variables are now highly significant variables. Macroeconomic fundamentals, here given with interest rate differentials are virtually unable to explain any of the fluctuation in the exchange rate. The similarity in conclusions we get for all four exchange rates are also stunning.[17]

5.1.3 Effect of including net options

As mentioned in subsection 4.1.3, options can be used to reduce exposure and risk. Correlation coefficients in table 3 suggested that this view was valid for the currency pairs of USD/CAD, USD/GBP and USD/JPY. The negative correlation coefficient implies that a positive order flow for foreign currency often corresponds with a negative net option position for the same foreign currency. The sum of order flow and net option position is lower than order flow itself.

As we would expect net option to have price impact on exchange rates as well, not including the net option position into the regression would in this case give an imprecise estimate of the true value for the order flow coefficient. I therefore choose to control for net option positions by including it into the model. I choose to include it together with regular order flow by

[17] It is not the "pre-whitening" process that caused this improvement in model fit. I have estimated models with "pre-whited" order flow but without uncertainty adjustment, and results were similar to those obtained for model [1] – [4].

summing order flow and net option position together as net options are measured in the same units. In this way I filter out hedging positions and get a potentially better proxy for speculative flow. Based on the discussion I call the sum of order flow and net option position to be net flow. Net flow measures the total price impact that order flow and net options have on exchange rates.

$$net\ flow_t = order\ flow_t + net\ options_t$$

As with order flow, I only concentrate on the unexpected net flows. Expected net flow should already be accounted for in the price. Based on the discussion and results in previous subsection I choose to adjust the net flows for uncertainty and market volume in the same manner as I did with order flows. I therefore "pre-white" the net flow according to the procedure explained in subsection 5.1.2 before adjusting them for uncertainty and price disagreement.

$$adj\ (unexpected)\ net\ flow_t = unexpected\ net\ flow_t * \ \vartheta_t * \omega_t$$

Augmented Dickey-Fuller test for non-stationarity in table 13 reveals that the null of non-stationarity can be rejected at 5% level for all four series. The "pre-whitening" of net flows enables me to include the level of the adjusted net flows directly into the model.

Table 13: *ADF test results for adjusted net flows*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Adj. net flow CAD	0.0068	-3.5898	8	14	187
Adj. net flow EUR	0.0012	-4.1096	9	14	185
Adj. net flow GBP	0.0000	-9.4565	2	14	194
Adj. net flow JPY	0.0152	-3.3249	12	14	184

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

The new models specified, [5] – [7] are identical to model [2-2] – [4-2] expect for the replacement of adjusted order flow with adjusted net flow as an explanatory variable in each of the models.

Model [5]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 adjusted\ net\ flow + \epsilon_t$

Model [6]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 interest\ diff_t + \beta_2 adjusted\ net\ flow_t + \epsilon_t$

Model [7]: $\Delta \log(exchange\ rate)_t = \beta_0 + \beta_1 \Delta(interest\ diff)_t + \beta_2 adjusted\ net\ flow_t + \epsilon_t$

The results of the regressions are given in table 14. I choose to use HAC standard errors since regression diagnostics in table C.5 suggest some heteroskedasticity in the residuals.

Table 14: *Portfolio Shift model estimation output, model [5] – [7]*

Regressor	Dependent variable: Δlog(USD/CAD)			Dependent variable: Δlog(USD/EUR)		
	[5]	[6]	[7]	[5]	[6]	[7]
$Constant$	-0.1932 (0.1462	-0.2075 (0.1453)	-0.1931 (0.1413)	0.0039 (0.2258)	-0.0984 (0.2660)	-0.0046 (0.2110)
$Interest\ diff$		-0.1248 (0.1248)			-0.2436 (0.1895)	
$Adj. net\ flow$	-0.0197*** (0.0043)	-0.0198*** (0.0043)	-0.0196*** (0.0041)	-0.0053* (0.0029)	-0.0052* (0.0027)	-0.0052 (0.0034)
$\Delta(Interest\ diff)$			0.0296 (0.4753)			-0.6228 (0.5489)
Diagnostics						
Adjusted R2	0.1924	0.1915	0.1966	0.0378	0.0455	0.0365
Observations	196	196	196	195	195	195

Regressor	Dependent variable: Δlog(USD/GBP)			Dependent variable: Δlog(USD/JPY)		
	[5]	[6]	[7]	[5]	[6]	[7]
$Constant$	-0.0428 (0.1758)	-0.0338 (0.2426)	-0.0721 (0.1646)	-0.1110 (0.2136)	-1.0325*** (0.3117)	-0.1077 (0.2221)
$Interest\ diff$		-0.0081 (0.1824)			-0.2640*** (0.0955)	
$Adj.\ net\ flow$	-0.0124*** (0.0039)	-0.0124*** (0.0037)	-0.0159*** (0.0046)	-0.1140*** (0.0411)	-0.1203*** (0.0392)	-0.1184*** (0.0411)
$\Delta(Interest\ diff)$			-1.5785*** (0.3713)			-1.3737 (0.8956)
Diagnostics						
Adjusted R2	0.0554	0.0505	0.0931	0.0588	0.0774	0.0724
Observations	197	197	197	197	197	197

Notes: All estimated coefficients and standard errors are multiplied with 100. HAC standard errors are given in brackets. Estimation sample: January 1994 – June 2010.
***, **, * indicates significance at 1% level, 5% level and 10% level

Comparing model [2-2] with model [5], the estimation results indicates that controlling for net options in the model improves the fit of the model for three of the exchange rates while the adjusted R-squared for the regression on GBP is almost unchanged. Price impact parameter is correctly signed and significant at a least 10% level in all cases, it is even significant at 1% significance level for three of the exchange rates. The size of the coefficient is virtually unchanged in the regressions of CAD, EUR and GBP.

We see similar patterns for the two other models, [6] and [7] were interest differentials are included. The adjusted R-squared are either unchanged or higher compared with model [3-2] and [4-2]. The price impact parameter of adjusted net flow is significant at 1% level for three of the exchanges rates while it is significant at 10% level for EUR in [6] before it turns insignificant in [7]. The impression I get from these results is that controlling for net options by including it as a sum with order flow improves the fit of the model and that net options positions have price impact on exchanges rates in the same manner as regular order flow of spot contracts. Recursive OLS estimates of the adjusted net flow coefficient in figure C.1, exhibit stability as well.

The adjusted net flow coefficients for the exchange rates of USD/CAD, USD/GBP and USD/JPY are larger than the corresponding adjusted order flow coefficients in the models [2-2] – [4-2]. As the net options and order flow for these three currencies pairs often exhibit negative correlation, omission of net options lead to an underestimation of the price impact parameter of adjusted order flow in the previous models. The new estimates suggest that adjusted net flow have largest price impact on the exchange rate of USD/JPY were an positive adjusted net flow of one trillion Yen decreases the USD/JPY by 12 basis points (bp). For USD/CAD, we have that one billion Canadian Dollar in adjusted net flow depreciates the USD/CAD rate by 2 bp. The other estimates suggest a price impact of adjusted net flow of roughly 1 bp for a billion worth of Pound Sterling and 0.5 bp for Euro. These estimates are somewhat lower than Chinn and Moore found with their dataset; 10 bp for USD/EUR and 18 bp for USD/JPY.

Based on analysis above, I therefore reach a second conclusion, namely that options also have explanatory power for exchange rates.[18] Adjusted R-squared increases and adjusted net flow coefficients are correctly signed and significant. Killen et al. (2006) states that the Portfolio shift model also implies a cointegration relationship between the level of exchange rate, interest differentials and cumulative order flow. Replacing order flow with adjusted net flow, I use Johansen test approach as described in section B.3 to test for Cointegration.

5.2 Testing for cointegration

According to Killeen et al. (2006), the Portfolio Shift model implies a cointegration relationship between the level of exchange rate, interest differentials and cumulative order flow. Chinn and Moore (2010) however argues that macroeconomic fundamentals should be included in the cointegration relationship implying a long run relationship between the level of exchange rate, cumulative order flow and macroeconomic "fundamentals". I test for cointegration using both models to check how my data fit with the models. In both models, I choose to replace unadjusted order flow with adjusted net flow based on the results from previous section. Consumer price difference is also included into the model of Chinn and Moore.

The test and estimation procedure is done in following steps:

- Set up the model as an unrestricted VAR and check for autocorrelation. Find the appropriate lag length and ensure that the residuals are white noise.

- If the model is well specified, I use the Johansen trace test to find number of cointegrating relationship. I choose to test for the case were a constant is included in the VAR and a constant and trend is included in the cointegration equation. As a robustness check I also test for cointegration when the trend is excluded from the cointegration equation.

[18] I have also tried to use order flow and net options as separate variables and adjusting these separate variables for liquidity and uncertainty (adjusted order flow and adjusted net option). The results for Portfolio Shift model when these two variables enter the OLS regressions separately are even better than the results when they enter as a sum and are given in table C.1 in the appendix. Both variables are highly significant and correctly signed in almost every the model, proving that net options positions also have price impact on exchange rates. The results suggest that the price impact effects of net options are between two and five times larger than price impact effect of order flow. However, treating the adjusted sum of order flow and net options are more in line with literature which only incorporate one flow variable.

- Estimate the Vector Error Correction Model if the test show cointegrating relationships.

Subsection 5.2.1 describes results for Johansen cointegration test for the Portfolio Shift model while subsection 5.2.2 analyses the Liquidity Shock model.

5.2.1 Portfolio Shift model

The variables included in the Portfolio Shift model are the level of exchange rate, interest differential and cumulative net flow. Interest differential and the level of exchange rate are I(1) variables as shown in earlier in this thesis. The cumulative series of adjusted net flow are also I(1) as table 15 tabulates.

Table 15: *ADF test results for cumulative adjusted net flows*

Series	Test statistic	P-value	Lag	Max lag	Observations in test equation
Cum. adj. net flow CAD	-1.2102	0.6699	9	14	186
Cum. adj. net flow EUR	-0.5055	0.8862	0	14	194
Cum. adj. net flow GBP	0.5627	0.9884	3	14	193
Cum. adj. net flow JPY	-1.7315	0.4137	13	14	183

Notes: constant included in test regression. The p-values given in EViews are according to MacKinnon (1996).

The unrestricted VAR is therefore a VAR with three variables. The number of lags which are included in VAR is determined by running the unrestricted VAR and comparing lag lengths by comparing information criterions. It is important that residuals exhibit white noise The Bayes Information Criterion (BIC) typically indicates a fairly short lag length for the VAR`s, ranging from one to two lags while the sequential Likelihood Ratio tests suggest a minimum lag length of five. Fixing the lag length to three seems to be appropriate to ensure serially uncorrelated residuals.

I test for cointegration using Johansen trace test as described in section B.3 and with a lag length of three for both test specifications. The results in table 16 indicate that the VAR of USD/JPY exhibit one cointegration relationship. The VAR of USD/GBP only have cointegration when I exclude the trend in the cointegration equation while the other VAR`s do not seem to exhibit cointegration.[19] Full test results are found in table B.2 in appendix B.4.

Table 16: *Number of cointegrating relationships for Portfolio Shift model*

Test specification	USD/CAD	USD/EUR	USD/GBP	USD/JPY
Constant in VAR, constant and trend in cointegrating equation	0	0	0	1
Constant in VAR and in cointegrating equation	0	0	1	1

Notes: null hypothesis is rejected if the p-value are lower than 0.05. Critical values in EViews are based on MacKinnon et al. (1999).

Based on these results, it seems hard to find cointegration when only adjusted net flow and interest differentials are included into the relationship. I therefore choose to include macroeconomic “fundamentals” into the cointegration vector, taking the view of Chinn and Moore (2010).

5.2.2 Liquidity Shock model

The variables included the cointegration relationship implied by the Liquidity Shock model are all integrated of order one (or higher): the log of the exchange rate, the cumulative adjusted net flow, interest rate differences, money supply differences, consumer price differences and industrial production differences.[20] The unrestricted VAR therefore includes six variables, where the macroeconomic fundamentals included, reflects a sticky-price monetary model since consumer price indices are included.

ADF tests suggested that money supply differences were I(2) for three of the countries, namely for Canada, euro area and Japan, but according to economic theory, I treat this variables as I(1). It is however worth to mention that the test approach described still can be adequate if money supply differences in fact were I(2). All variables included in the VECM,

[19] This results also confirms the suspicion that interest differentials are I(1) as I assumed earlier, since inclusion of a I(0) variable would create a cointegration relationship on its own according to Kennedy (2008). Since the Johansen test did not detect any cointegration for the case of USD/CAD and USD/GBP, I am able to dismiss that interest differentials for these two cases are I(0) even though ADF-tests in table 6 suggested that this was the case.

[20] I choose to insert macroeconomic fundamentals as differentials from foreign country against the U.S. instead of including each separately, as is common in literature. The rationale for this is that the countries of interest in this thesis are quite similar, and the coefficient estimates should accordingly be in the same range.

should be I(1) or higher. Since the Johansen test procedure test whether the lagged vector of the endogenous variable are I(0), the test is still valid if I include I(2) together with I(1) variables. It is possible that there exists a relation between I(2) and I(1) variables which is I(0). Hence the validity of the Johansen test is not threatened by including the money supply difference for the VAR`s of Canada, euro area and Japan.

As in the case with Portfolio Shift model, the Bayes Information Criterion (BIC) indicates a short lag length of one in all the VAR`s while sequential Likelihood Ratio tests and Final Prediction Error suggest seven to eight lags. By inspection, it seems that residuals exhibit serial correlation when three or fewer lags are included. Running the VAR`s with four lags instead, residuals seems to correspond to a white noise process. For the VAR of USD/JPY, I fix the lag length to five as the VECM estimation with four lags produced implausible results for the long run coefficient of cumulative adjusted net flow. The VAR of USD/EUR is also fixed to a lag length of five since the Johansen test suggested six cointegrating relationships for the VAR with four lags.

Using the Johansen trace test on the VAR`s with lag lengths of four and five, I find that the Liquidity Shock model implies a least one cointegration relationship for all four exchange rates. For the case were a trend is included in the cointegrating equation, I find one cointegrating vector for three of the VAR`s at 5% critical value. The robustness of this result is not altered when the trend in the cointegrating equation is excluded. The results are given in table 17, while full test results are given in table B.3 in appendix B.4.

Table 17: *Number of cointegrating relationships for Liquidity Shock model*

Test specification	USD/CAD	USD/EUR	USD/GBP	USD/JPY
Constant in VAR, constant and trend in cointegrating equation	1	4	1	1
Constant in VAR and in cointegrating equation	2	3	1	2

Null hypothesis is rejected if the p-value are lower than 0.05. Critical values in EViews are based on MacKinnon et al. (1999).

The results are encouraging and suggest that cumulative adjusted net flow and the exchange rate are cointegrated and that cumulative adjusted net flow have an important role for determining the long term exchange rate, but only in combination with monetary fundamentals. As the Liquidity Shock model only implies one cointegrating vector, I proceed by estimating the VECM for the case of USD/EUR with only one cointegrating vector[21] even if the Johansen test suggest four cointegrating vectors. The next subsection inspects the VECM estimation results for the four exchange rates when one cointegrating vector is implied.

5.2.3 VECM estimation results for Liquidity Shock model

Having found a one cointegrating relationship for each exchange rate, I proceed to estimate four VECM`s based on the VAR`s, all with one cointegrating relationship. Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) suggest that a trend should be included in the cointegration equation for all four exchange rates when estimating the VECM. The cointegration equation with a trend is written out as:

$$\begin{aligned}\varepsilon = \beta_1 \log(exchange\ rate) + \beta_2 interest\ diff + \beta_3 cumulative\ adj.net\ flow \\ + \beta_4 IPR\ diff + \beta_5 money\ diff + \beta_6 CPI\ diff + \beta_7 trend + constant\end{aligned}$$

The normalization of log exchange rate implies $\beta_1 = 1$. It can furthermore be rewritten to an equation for the log exchange rate.

$$\begin{aligned}&\log(exchange\ rate) \\ &\quad = -\beta_2 interest\ diff - \beta_3 cumulative\ adj.net\ flow - \beta_4 IPR\ diff \\ &\quad - \beta_5 money\ diff - \beta_6 CPI\ diff - \beta_7 trend - constant\end{aligned}$$

We would expect that a negative long run relationship between cumulative adjusted net flow and the level of exchange rate. In other words; β_3 should be positive. The cointegrating vector implied by Johansen procedure for all four cases are tabulated in table 18. Cumulative adjusted net flow is correctly signed in all four cases. T-tests of the variables imply that cumulative adjusted net flow cannot be excluded from the cointegrating relationship for three of the cases (USD/CAD, USD/GBP and USD/JPY). This result highlights the connection between adjusted net flow and exchange rates, implying that adjusted net flow have a persistent and long-lived effect on the exchange rate as found in earlier studies (Bjønnes and Rime 2005; Killeen et al. 2006; and Chinn and Moore 2010).

[21] This procedure is also done in Chinn and Moore (2010).

Table 18: *Cointegrating vectors from Johansen procedure*

	USD/CAD	USD/EUR	USD/GBP	USD/JPY
β_2	2.2122**	-7.0562***	-3.6589**	47.5823***
	(1.0230)	(2.0120)	(1.7850)	(16.8620)
β_3	0.0588***	0.0106	0.1483***	6.5861***
	(0.0061)	(0.0069)	(0.0190)	(1.2240)
β_4	2.5117***	1.1691**	0.5424***	37.2440***
	(0.2680)	(0.5890)	(0.1460)	(5.9650)
β_5	-0.7196**	0.5447	3.6924***	-24.2852***
	(0.3090)	(1.1590)	(0.8330)	(5.8560)
β_6	2.5628**	27.0054***	16.9726***	-131.5358***
	(1.2810)	(3.3680)	(2.1380)	(23.1410)
β_7	0.8804***	1.6787***	0.6050***	-16.4977***
	(0.1270)	(0.2270)	(0.2140)	(6.3470)
Constant	-53.7757	-23.5266	41.8532	-78.9339

Notes: all coefficients (except β_1 which is normalized to 1) and standard errors have been multiplied by 100.
Trend in cointegrating vectors starts in January 1994. ***,**.* indicates significance at 1%, 5% and 10% level.

Since I have multiplied the coefficients within the cointegrating vector by 100, the β_3 coefficients can be interpreted as percentage points change in the exchange rate for each billion/trillion worth of cumulative adjusted net flow. The coefficients suggest that an increase in cumulative adjusted net flow of one billion worth of CAD decreases the price of USD measured in CAD by 5 bp, whereas the corresponding effect for Pound Sterling is almost 15 bp. For USD/EUR, the effect is smaller; only 1 bp per billion euros, but this estimate is insignificant. These estimates are all within the range of previous long run estimates in the literature. Killen et al. (2006) reports of a long run price impact of 3 bp for the exchange rate of DEM/FF[22], but this result is obtained with daily data.

For USD/JPY I find that the exchange rate falls with over 6 percentage points for each trillion worth of cumulative adjusted net flow. Given the size, this estimate seems implausible. A possible solution to this, proposed and done by Chinn and Moore (2010), is to estimate this

[22] FF: French franc

relationship using single equation methods such as Dynamic OLS (DOLS)[23] or Fully Modified OLS in order to obtain more reliable results. Using DOLS, I find that the long run price impact effect for cumulative adjusted net flow is 12.5 bp[24] per trillion worth of JPY in adjust net flow.

Comparing the long run price impact of adjusted net flow with the short run effects found from the Portfolio Shift model in table 14, I observe that the long run effects are larger than the short run effects, implying an “undershooting” adjustment mechanism for the exchange rates. The exchange rates are rigid in their adjustment and there is presence of “learning effects”. Agents are slow learners and it takes time for them to revise their beliefs based on adjusted net flow and act correspondingly.

This corresponds well with the fact that the Treasury Bulletin is released on a quarterly basis. While interdealer order flow is available at the end of the day, the flow statistic from Treasury Bulletin comes only four times a year, which implies that agents only can infer the information embedded in the adjusted net flow with a couple of months lag. Since the agents only are able to observe adjusted net flow with some delay, the full price impact is not reached instantaneously, implying that the long run price impact of adjusted net flow are larger than the short run price impact. For USD/JPY, this effect is small however, as the short run effect is 12 bp per trillion while the long run impact is 12.5 bp per trillion. The graphs of the cointegrating vectors based on the Johansen procedure are displayed in figure 6.

[23] Estimation procedure developed by Stock and Watson (1993).
[24] The estimation results are tabulated in table C.2.

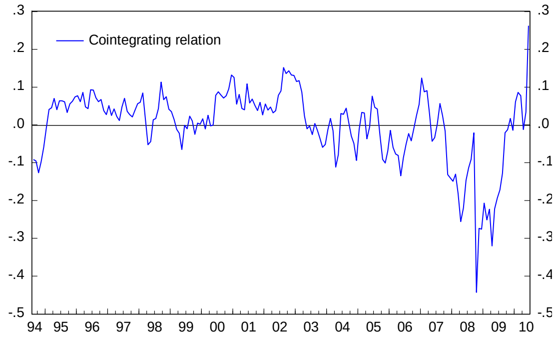


Figure 6 a: For USD/CAD

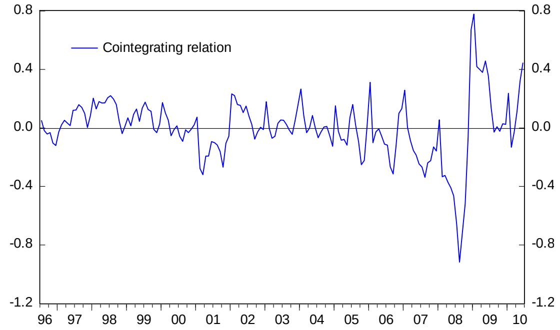


Figure 6 b: For USD/EUR

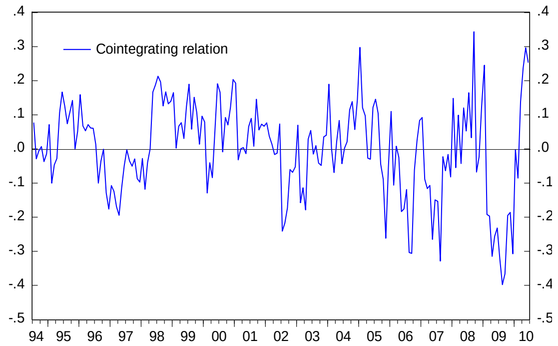


Figure 6 c: For USD/GBP

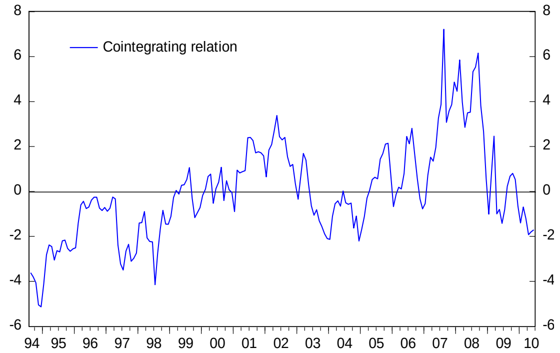


Figure 6 d: For USD/JPY

Figure 6: *Cointegrating relationship implied by VECM estimation of Liquidity Shock model with one cointegration relationship implied. January 1994 - June 2010 (January 1996 – June 2010 for USD/EUR).*

Having found the cointegrating vector, I would also like to see if the equilibrium adjustment coefficients in the exchange are negative. A negative coefficient implies that the exchange rate is brought back to equilibrium in case of discrepancy from the long run relationship. Table 19 displays the VECM estimation output for the change in log of exchange rate in all four VECM`S. The estimation output for the other endogenous variables in the system is not tabulated since they are not of interest in this case. The equilibrium adjustment coefficients are correctly signed in all cases and significant at 5% level for three of the exchange rates. For USD/CAD, 5% of the deviation from the equilibrium exchange rate is adjusted during each month, while the same number is 7% and 3% for USD/EUR and USD/GBP respectively. The equilibrium adjustment coefficient is small in the case of USD/JPY, implying only 0.5% correction towards equilibrium each month. As consequence of the implausible long run coefficient of cumulative adjusted net flow above, I propose to discard the VECM estimation results for this exchange rate.

The diagnostics in table 19 reveals that the models are well specified and that the VECM`s are able to explain from between 7% to 14% of the variation in the spot exchange rate. This is an improvement compared to the adjusted R-squared obtained with the Portfolio Shift model for all exchange rates except the case with USD/CAD.

Table 19: *VECM estimation results for the change in log of exchange rates*[a]

	Δlog(USD/CAD)	Δlog(USD/EUR)	Δlog(USD/GBP)	Δlog(USD/JPY)
Cointegrating relationship	-5.3743**	-6.8646***	-2.7071	-0.4597***
	(2.7120)	(2.4320)	(1.7230)	(0.1540)
Constant	0.0011	0.1152	0.4707**	-1.4197**
	(0.2110)	(0.2730)	(0.2180)	(0.5560)
Δ(Cumulative adj. net flow(-1))	-0.0018	-0.0002	0.0031	0.0306
	(0.0043)	(0.0023)	(0.0064)	(0.0350)
Δ(Cumulative adj. net flow(-2))	0.0003	-0.0023	0.0058	-0.0197
	(0.0045)	(0.0024)	(0.0059)	(0.0350)
Δ(Interest diff.(-1))	-0.0911	-0.5119	-1.4947**	0.6882
	(0.6790)	(1.0480)	(0.6940)	(0.8060)
Δ(Money diff.(-1))	-0.2075**	-0.2662	-0.5377***	0.0080
	(0.1690)	(0.2180)	(0.1440)	(0.2380)
Δ(IPR diff.(-1))	0.7943***	0.3004	0.1650	-0.0860
	(0.2270)	(0.2140)	(0.1450)	(0.1400)
Δ(CPI(-1))	0.8780	0.0885	0.2136	-1.6054***
	(0.5660)	(0.6820)	(0.3840)	(0.5430)
Diagnostics				
Adjusted R-squared	0.0938	0.0702	0.1319	0.1467
LM(10)[b]	34.4467	36.9899	32.1792	40.5763
	[0.5425]	[0.4230]	[0.6510]	[0.2756]
Q(36)[c]	1189.348	1130.420	1214.808	1177.585
	[0.4428]	[0.6308]	[0.2540]	[0.2589]

[a] All coefficients and standard errors in VECM are scaled by 100. Only the first lag of the endougenous variables are tabulated in this table. Two lags of adjusted net flow are tabulated. Estimation sample: January 1994 – June 2010 (January 1996 – June 2010 for EUR). ***,**.* indicates significance at 1%, 5% and 10% level.

[b] Lagrange Multiplier test for autocorrelation of order 10. P-values of rejecting null of no serial correlation are given in square brackets.

[c] Ljung-Box test for autocorrelation of order 36. P-values of rejecting null of no serial correlation are given in square brackets.

Conclusion based on the results obtained in this subsection is that adjusted net flow seems to have a persistent and long lived effect on exchange rates as described in literature, but only together with macroeconomic fundamentals following the view of Chinn and Moore, (2010). It is interesting that microstructure seems applicable even at monthly level of frequency.

All exchange rates seem to be reverting towards equilibrium, confirming some form of a long run relationship. The long run coefficients for adjusted net flow suggest that the long run price impact ranges between 1 to 15 basis points depending on the currencies involved. The model fit obtained with Liquidity Shock model is slightly better than those obtained with the Portfolio Shock model in previous section, measured by adjusted R-squared.

As a good in-sample fit does not necessary translate into a good out-of-sample fit (Chinn and Moore, 2010), it would be interesting to see how this model with adjusted net flow performs in out-of-sample forecasting. I will however leave this to later work.

6 Conclusions

This thesis has utilized the microstructure framework to explain movements in monthly spot exchange rates. The focus have been put on four major exchange rates; USD/CAD, USD/EUR, USD/GBP and USD/JPY. The Portfolio Shift model (Evans and Lyons 2002; Killeen et al. 2006) and the Liquidity Shock model (Chinn and Moore, 2010) have been used for this purpose. Focusing on monthly data, this thesis is a continuation of recent work conducted by Chinn and Moore (2010) at this level of frequency. As microstructure normally have focused on high frequency data, this thesis provides more empirical evidence that microstructure exchange rate models are applicable to lower frequencies as well, filling a hole which classical macroeconomic models have shown unable to explain.

As my findings suggest, there is a close relationship between the amount of information that order flow carry and exchange rate volatility. Using rolling regressions I find that order flow is more informative during times of high exchange rate volatility and that the price impact parameter increases with volatility as stated in Killen et al. (2006). By modeling order flow according to the theoretical foundations established in Killeen et al. (2006), I manage to improve model fit for all four exchange rates. Adjusting order flow for uncertainty and price disagreement measured by the volume, I find that adjusted order flows are able to explain a higher proportion of exchange rate movements than unadjusted order flow. I also find that option positions have explanatory power on exchange rates, and controlling for this improves model fit. Adjusted net flow itself is able to explain up to almost twenty percent of movements for the exchange rate of USD/CAD.

Furthermore, cointegration analysis suggests that adjusted net flow is cointegrated with the exchange rate, but that macroeconomic fundamentals probably should be incorporated into the relationship as well. This implies that adjusted net flow have a long lived and permanent effect on exchange rates, rejecting the theory that order flow only have transitory price effect. VECM estimates also suggest that the exchange rates considered in this thesis moves toward an equilibrium level. The long run price impact of adjusted net flow is larger than the short run effects for all the exchange rates, indicating that there is an "undershooting" adjustment mechanism for the exchange rates.

This corresponds well with the fact that the Treasury Bulletin is only published four times a year, implying that agents only can infer the information embedded in the adjusted net flow with some lag. Agents are slow to revise their beliefs because of this information lag and act correspondingly. The results obtained in this thesis have also for the most part been robust across the different exchange rates of interest.

There are several directions future work could be directed towards. First, out-of-sample forecasts could be created from the Liquidity Shock model with adjusted net flow to check the forecast performance of this model. As a good in-sample fit does not necessary translate into good out-of-sample fit, it would be interesting to see how out-of-sample forecast from with adjusted net flow would perform against other exchange rate models and against a random walk model. Another natural extension would be to check the validness of the findings in this thesis for other exchange rates as well as at other frequencies. The rationale for uncertainty adjustment is well documented in the literature (Killeen et al., 2006) and should at least be fruitful for data with higher frequency than monthly.

As I have made one critical assumption regarding the sign of the order flow stemming from net purchase positions, I would also like to see if the results in this thesis are valid with order flow following the strict definition as stated in Lyons (2001).

References

Bacchetta, P. and E. Van Wincoop (2006): "Can information heterogeneity explain the exchange rate determination puzzle?", *American Economic Review*, vol. 96, 552-576.

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

BIS (2010): Triennial Central Bank Survey: Report on global foreign exchange market activity in 2010, Bank for International Settlements, Basel.

Bjønnes, G. H., D. Rime (2005): "Dealer Behavior and Trading Systems in Foreign Exchange Markets", *Journal of Financial Economics*, vol. 75, 571-605.

Bjønnes, G. H., D. Rime and H. O. A. Solheim (2005): "Liquidity Provision in the Overnight Foreign Exchange Market", *Journal of International Money and Finance*, vol. 24, 175-196.

Bodie, Z., A. Kane and A. J. Marcus (2009): Investments (8 ed.), McGraw-Hill Irwin, New York.

Cao, H. H., M. D. Evans and R. K. Lyons (2006): "Inventory Information", *Journal of Business*, vol. 79, 325-364.

Chinn, M. D. and M. J. Moore (2010): "Private Information and the Monetary Model of Exchange Rates: Evidence from a Novel Data Set", Working Paper.

Den Haan, W. J. and A. Levin (1998): "Vector Autoregressive Covariance Matrix Estimation", University of California, San Diego, manuscript.

Dickey, D. A. and W. A. Fuller (1979): "Distribution of the Estimators for Autoregressive Time Series With a Unit Root", *Journal of the American Statistical Association*, vol. 366, 427-431.

Dornbusch, R. (1976): "Expectations and Exchange Rate Dynamics", *Journal of Political Economy*, vol. 84, 1161-1176.

Engle, R. F. (1982): "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", *Econometrica*, vol. 50, 987-1007.

Engle, R. F. and C. W. J. Granger (1987): "Co-Integration and Error Correction: Representation, Estimation and Testing", *Econometrica*, vol. 55, 251-276.

Evans, M. D. D. (2011): "The Microstructure of Currency Markets", forthcoming in the *Encyclopedia of Financial Globalization*.

Evans, M. D. D. and R. K. Lyons (2002): "Order Flow and Exchange Rate Dynamics", *Journal of Political Economy*, vol. 110, 170-180.

Frankel, J. A. and A. K. Rose (1995): "Empirical Research on Nominal Exchange Rates", in Handbook of International Economics vol. 3, edited by G. M. Grossman and K. S. Rogoff, North-Holland.

Fuller, W. A. (1976): Introduction to Statistical Time Series, John Wiley and Sons, New York.

Granger, C. W. J. and P. Newbold (1974): "Spurious Regression in Econometrics", *Journal of Econometrics*, vol. 2, 111-120.

Greene, W. H. (2008): Econometric Analysis (6 ed.), Pearson Prentice Hall.

Hill, R. C., W. E. Griffiths and G. C. Lim (2008): Principles of Econometrics (3 ed.), John Wiley & Sons, New York.

Hendry, D. F. and B. Nielsen (2007): Econometric Modeling, Princeton University Press, Princeton.

Jarque, C. M. and A. K. Bera (1980): "Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals", *Economic Letters*, vol. 6, 255-259.

Johansen, S. (1988): "Statistical Analysis of Cointegration Vectors", *Journal of Economic Dynamics and Control*, vol. 12, 231-254.

Johansen, S. (1995): Likelihood-Based Inference in Cointegrated Vector Autoregressive Models, Oxford University Press.

Kennedy, P. (2008): A Guide to Econometrics (6 ed.), Blackwell Publishing.

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

Lyons, R. K. (2001): The Microstructure Approach to Exchange Rates, MIT Press.

MacKinnon, J.G. (1996): "Numerical Distribution Functions for Unit Root and Cointegration Tests", *Journal of Applied Econometrics*, vol. 11, 631-653.

MacKinnon, J.G., A. A. Haug and L. Michelis (1999): “Numerical Distribution Function of Likelihood Ratio Tests for Cointegration”, *Journal of Applied Econometrics*, vol. 14, 563-577.

Meese, R. A. and K. Rogoff (1983a): “Empirical Exchange Rate Models of the Seventies: Do they fit out of sample”, *Journal of International Economics*, vol. 14, 3-24.

Meese, R. A. and K. Rogoff (1983b): “The Out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification”, in Exchange Rate and International Macroeconomics, edited by J. Frenkel, University of Chicago Press.

Newey, W. K. and K. D. West (1987): “A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”, *Econometrica*, vol. 55, 703-708.

Ng, S. and P. Perron (1995): “Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag”, *Journal of the American Statistical Association*, vol. 90, 268-281.

Obstfeld, M. and K. Rogoff (2000): “The Six Major Puzzles in International Macroeconomics: Is there a Common Cause?”, NBER Working paper.

Payne, R. (2003): “Informed trade in spot foreign exchange markets: an empirical investigation”, *Journal of International Economics*, vol. 61, 307-329.

Rime, D. (2001): “U.S. Exchange Rates and Currency Flows”, Institute for Financial Research, SIFR Research Report Series 4.

Rime, D. and E. Sojli (2006): “Order flow analysis of exchange rates”, *Norges Bank Economic Bulletin*, vol. 77, 147-152.

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

Rogoff, K. (2009): “Exchange rates in the modern floating era: what do we really know?”, *Review of World Economics*, vol. 145, 1-12.

Schwert, G. W. (2002): “Tests For Unit Roots: A Monte Carlo Investigation”, *American Statistical Association*, vol. 20, 5-17.

Stock, J. H. and M. W. Watson (1993): “A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems, *Econometrica*, vol. 61, 783-820.

Stock, J. H. and M. W. Watson (2007): Introduction to Econometrics (2 ed.), Pearson Addison Wesley.

Sydsæter, K. and B. Øksendal (2006): Lineær Algebra, Gyldendal Norsk Forlag AS 2004.

TB (2010): The Treasury Bulletin December 2010. Financial Management Service, Washington D.C.

Tranvåg, H. J. (2009): "Uncovered Interest Rate Parity and the Time-Varying Foreign Exchange Risk Premium", Master thesis in Financial Economics at NTNU.

White, H. (1980): "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", *Econometrica*, vol. 48, 817-838.

Williamson, J. (2009): "Exchange Rate Economics", *Open Economies Review*, vol. 20, 123-146.

A Data

A.1 Descriptive statistics

Table A.1: *Descriptive statistics for order flows*

	CAD	EUR	GBP	JPY
Mean	-17.6088	21.9059	-4.8821	-12.9382
Median	-7.5650	-9.3456	4.7145	-13.1495
Maximum	50.6470	478.7570	93.6050	23.7210
Minimum	-172.9410	-402.3230	-145.0850	-51.7710
Std. Dev.	42.8533	176.4410	46.7570	10.7266
Skewness	-1.1235	0.4942	-0.6196	0.5744
Kurtosis	4.1476	2.9615	2.9558	5.1160
Observations	198	198	198	198

Table A.2: *Descriptive statistics for net option positions*

	CAD	EUR	GBP	JPY
Mean	-4.0035	-1.6860	5.6547	3.5477
Median	-3.3350	0.5990	4.2460	3.4255
Maximum	32.1470	43.7900	45.0340	15.1100
Minimum	-24.5660	-58.7520	-16.0250	-7.4320
Std. Dev.	9.9067	23.1419	7.5963	3.5185
Skewness	0.5789	-0.3082	1.5479	0.1321
Kurtosis	4.1871	2.2274	7.5624	4.7500
Observations	198	198	198	198

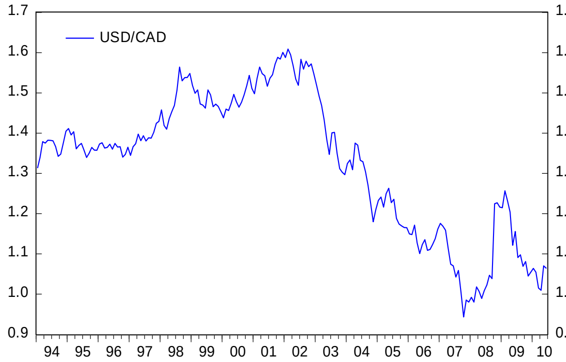
Table A.3: *Descriptive statistics for the exchange rates*

	USD/CAD	USD/EUR	USD/GBP	USD/JPY
Mean	1.3265	0.8603	0.6086	111.3010
Median	1.3652	0.8283	0.6166	111.2050
Maximum	1.6088	1.2092	0.7071	144.1300
Minimum	0.9436	0.6312	0.4805	83.5600
Std. Dev.	0.1745	0.1321	0.0586	11.7978
Skewness	-0.3967	0.7293	-0.3690	-0.0133
Kurtosis	2.0697	2.8391	2.2845	2.9407
Observations	198	198	198	198

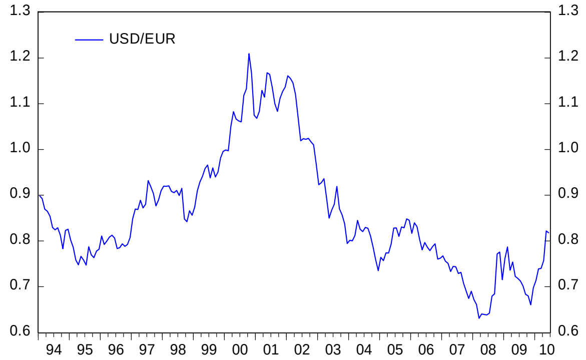
Table A.4: *Descriptive statistics for the interest differentials*

	Interest diff. CAD	Interest diff. EUR	Interest diff. GBP	Interest diff. JPY
Mean	-0.1078	-0.3716	1.1211	-3.4781
Median	-0.1100	-0.3037	0.8350	-4.1550
Maximum	2.1200	3.0650	3.3500	0.1100
Minimum	-2.6800	-2.8800	-0.7800	-6.6400
Std. Dev.	1.0532	1.3868	1.0878	1.8787
Skewness	-0.0152	0.1430	0.3325	0.3408
Kurtosis	2.7471	1.9436	2.0314	1.7561
Observations	198	198	198	198

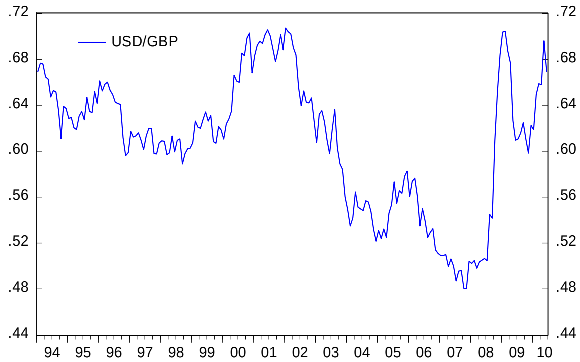
A.2 Graphs



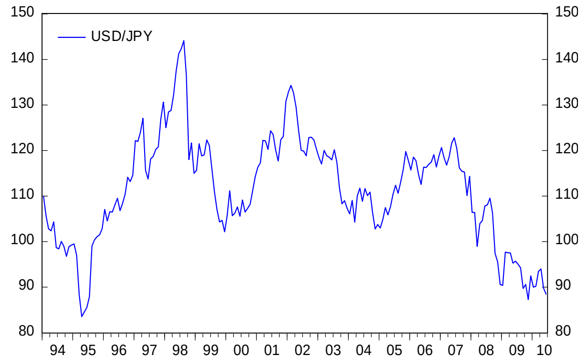
A.1 a: USD/CAD



A.1 b: USD/EUR



A.1 c: USD/GBP



A.1 d: USD/JPY

Figure A.1: *Exchange rates, measured in units of foreign currency per USD. Monthly data, spot rates. January 1994 – June 2010.*

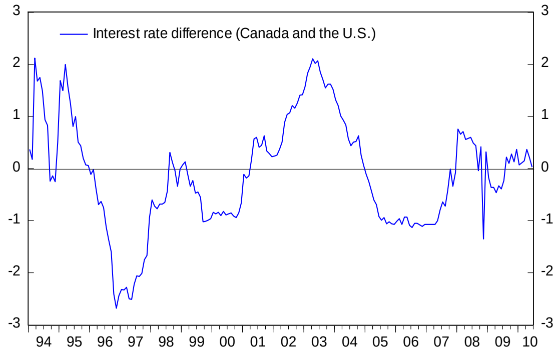


Figure A.2 a: Between Canada and the U.S.

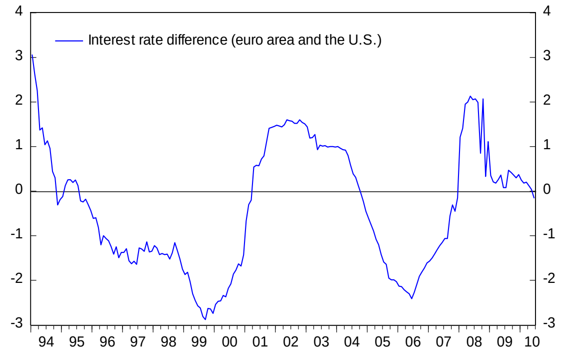


Figure A.2 b: Between Euro area and the U.S.

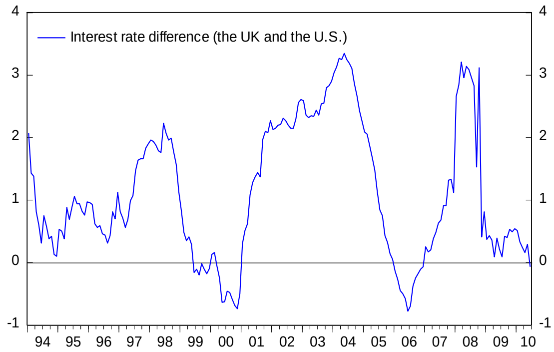


Figure A.2 c: Between the UK and the U.S.

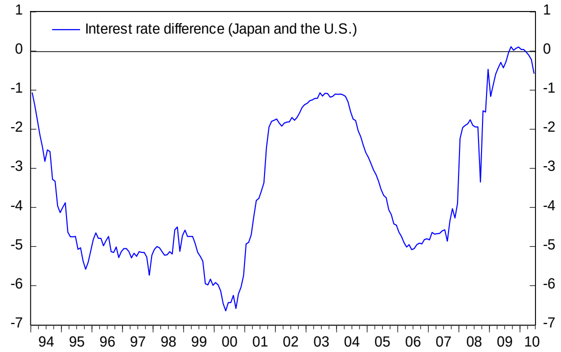


Figure A.2 d: Between Japan and the U.S.

Figure A.2: *Interest difference for 3 month deposit rates between four countries and the U.S. Percentage points. January 1994 – June 2010.*

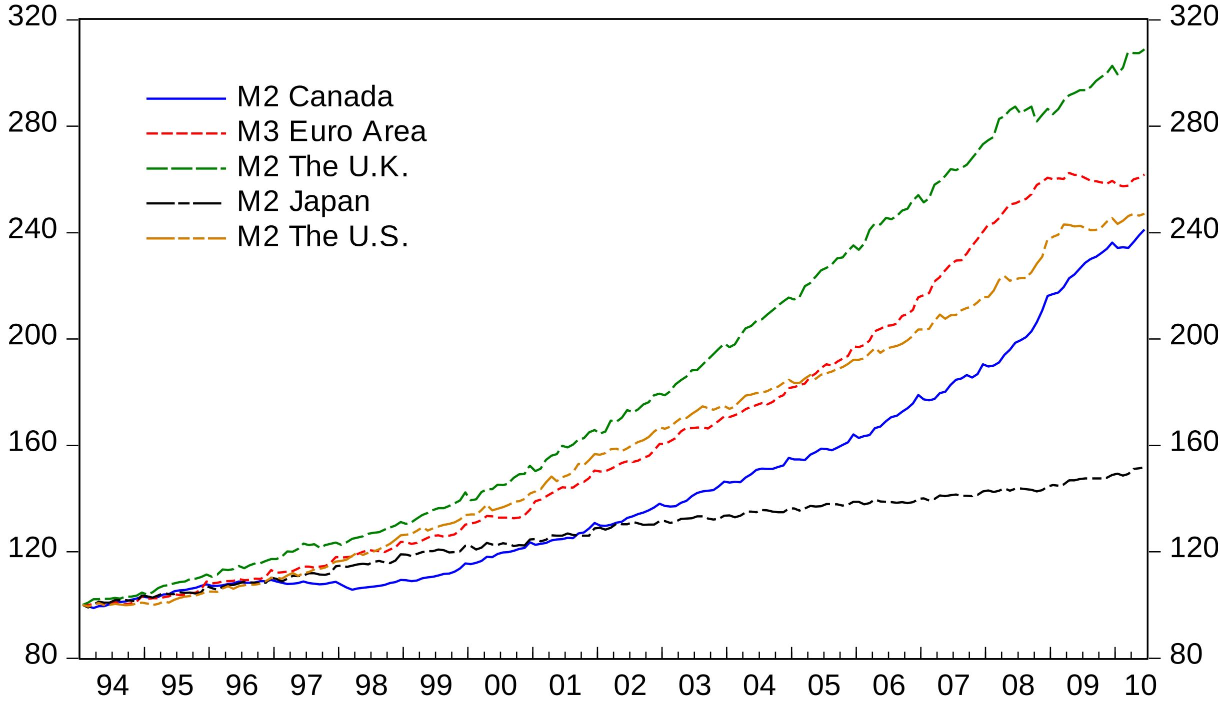


Figure A.3: *Money supply, normalized to be 100 in January 1994. January 1994 – June 2010.*

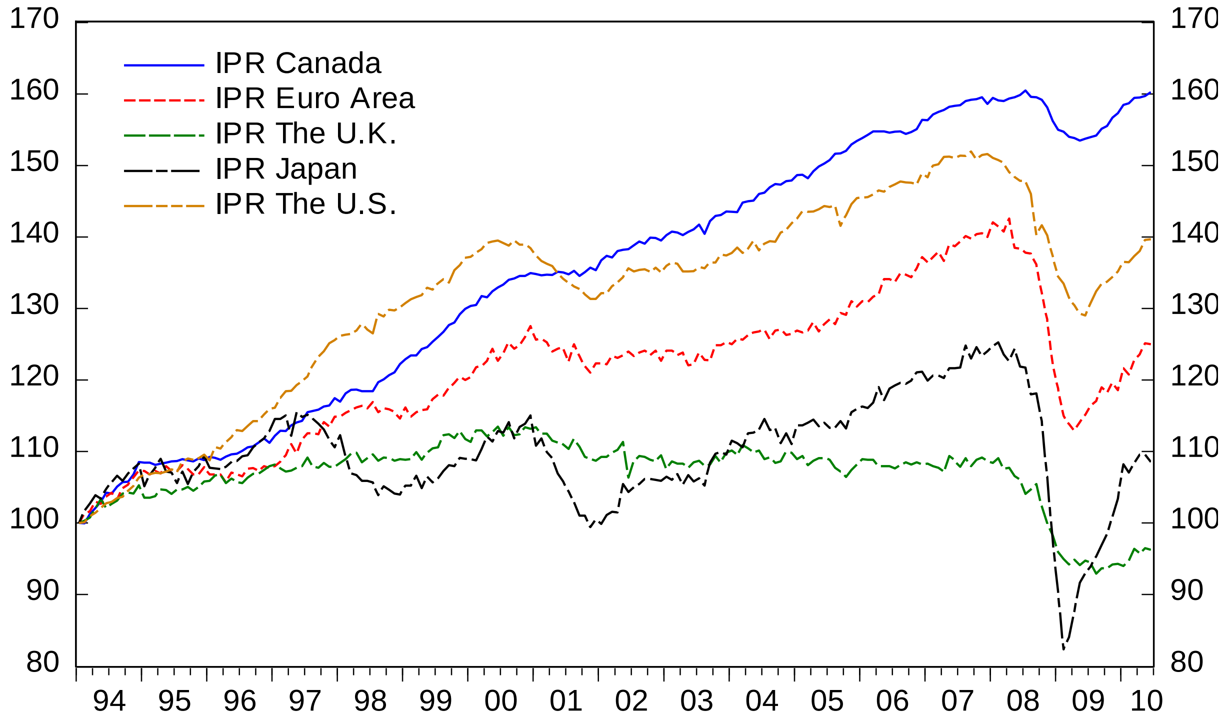


Figure A.4: *Industrial production, normalized to 100 in January 1994. January 1994 – June 2010.*

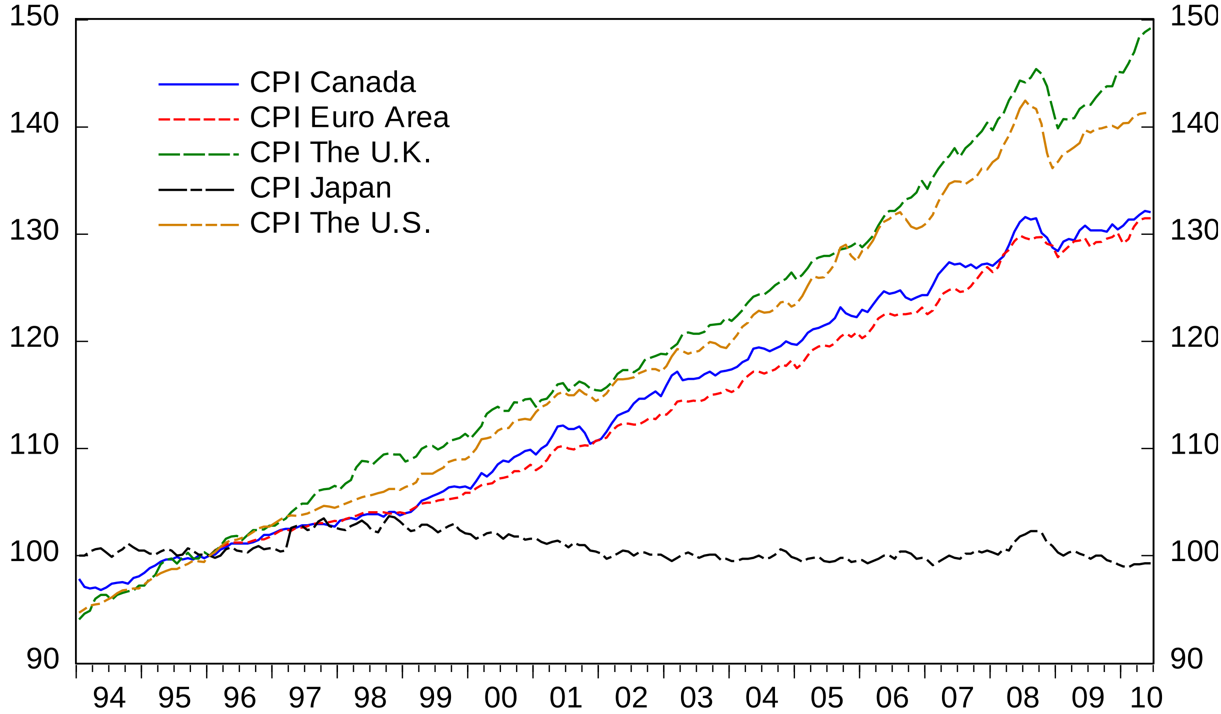


Figure A.5: *Consumer price index, normalized to 100 in January 1996. January 1994 – June 2010 (January 1996 – June 2010 for euro area).*

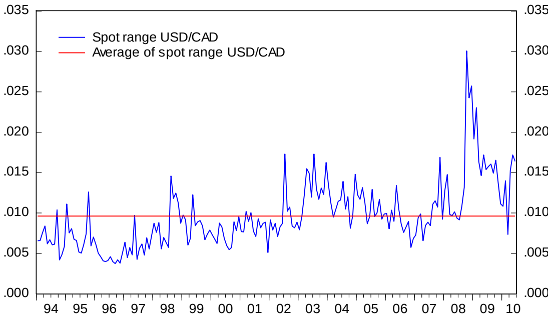


Figure A.6 a: Spot range USD/CAD

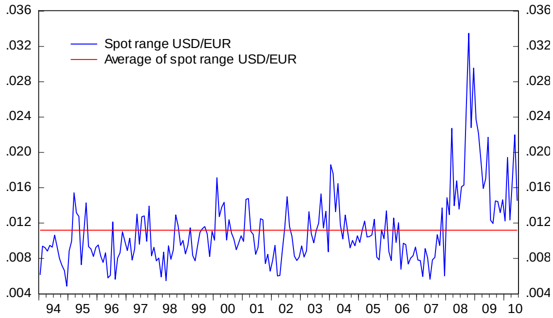


Figure A.6 b: Spot range USD/EUR

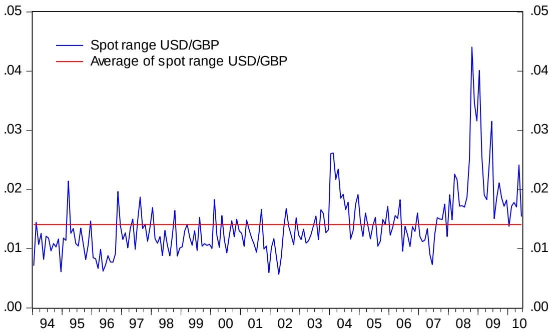


Figure A.6 c: Spot range USD/GBP

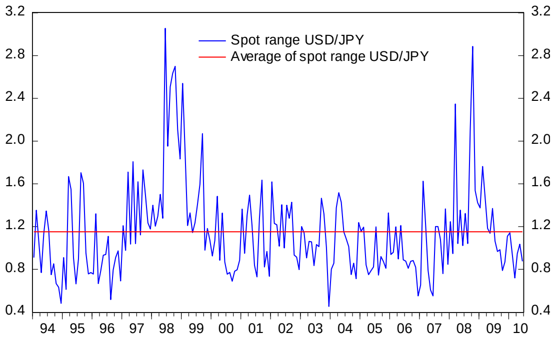


Figure A.6 d: Spot range USD/JPY

Figure A.6: *Spot range for exchange rates of USD/CAD, USD/EUR, USD/GBP and USD/JPY. January 1994 – June 2010.*

B Basic time series econometrics

This section reviews the concepts and methods for time series econometrics used in this thesis. For readers known with time series econometrics, most of this will be familiar readings. Section B.1 will go through the concept of unit root, non-stationary variables and a test we can apply in order to check the order of integration. Section B.2 will go through the concept of cointegration and explain the Engle-Granger two step method of testing for cointegration. Section B.3 introduces the Vector Error Correction Model (VECM) and its close affiliation with cointegration testing and the Johansen test procedure.

B.1 Unit roots and non-stationary variables

In time series econometrics, we often distinguish between two types of series, stationary series and non stationary series. Conceptually, a series is stationary if its mean and variance are constant over time, in other words the distribution is time independent. These types of series often seem to fluctuate around a mean (Stock and Watson, 2007).

Let us consider a simple autoregressive process of first order, an AR(1) process.

$$Y_t = \beta Y_{t-1} + \epsilon_t$$

In order for this series to be stationary, we need the unconditional expectation, variance and autocorrelation to be (Hendry and Nielsen, 2007):

$$E(Y_t) = 0 \qquad VAR(Y_t) = \frac{\sigma^2}{1-\beta^2} \qquad CORR(Y_t, Y_{t-s}) = \beta^s$$

With stationary series, the effects of a shock will as time goes by slowly die out. The effects are temporary. This is equivalent as saying $|\beta| < 1$. However, we also often face non stationary series when conducting time series econometrics. These types of series are characterized by clear trends in the series and they do not look like they fluctuate around some values. Moreover, the effects of a shock are infinite and will never die out. This is equivalent to $|\beta| = 1$ (Hendry and Nielsen, 2007).

Stationary series are integrated of order zero. It is common to denote a time series that is integrated of order p with I(p). Stationary series are therefore I(0), while non-stationary series have higher order of integration. We could lower the level of integration by differencing the series, each difference will lower the order of integration by 1. If Y_t is integrated of order (1), then the difference of this series, $\Delta Y_t = Y_t - Y_{t-1}$ is I(0). If Y_t are I(2), then ΔY_t will be I(1).

The distinction between stationary and non-stationary series is important for several reasons as Stock and Watson (2007) mentions. With non-stationary series, we cannot rely on the estimators and test statistics of having their usual large sample normal distribution. Hence the standard t-test cannot be conducted in case of non-stationarity. Another caveat when dealing with I(1) or higher order of integrated series is the problem called spurious regression as stated in Granger and Newbold (1974). This could happen if we regress a I(1) series on another I(1) and they seem related when they in fact are not. These problems ensure the necessity of being cautious when dealing with time series data.

Dickey and Fuller developed a formal test of non-stationarity (Fuller 1976; Dickey and Fuller 1979). I will use the Augmented Dickey-Fuller test, also known as the ADF test to test my data for non-stationarity. This test is based on a AR(p) process:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + \epsilon_t$$

This equation could easily be rewritten to:

$$\Delta Y_t = \beta_0 + \phi Y_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta Y_{t-j} + \epsilon_t$$

where $\phi = \sum_{i=1}^{p} \beta_i - 1$ and $\gamma_j = -\sum_{k=j+1}^{p} \beta_k$.

In order to test for non-stationarity, we test whether $\phi = 0$, or equivalent that $\sum_{i=1}^{p} \beta_i = 1$, in which case we have non stationarity. Hence the ADF test are conducted with $H_0: \phi = 0$ $H_1: \phi > 0$. As mentioned above, in the case of non stationarity, we cannot use the critical values from the normal distribution. The appropriate statistics to use is called Dickey-Fuller statistic and the critical values are derived from simulation experiments. The values are described in Fuller (1976) and are dependent on how we specify the test. We have the option of including a constant, a deterministic trend or both in the ADF-equation. It is also dependent of the number of observations.

Using EViews in my computations, the program automatically returns the 10%, 5% and 1% Dickey-Fuller critical values according to number of observations and test specifications. With almost 200 observations in all my series, close approximations to the exact Dickey-Fuller values can be found in good econometric books, example given in Hamilton (1994). The test specification is specified in all the unit root test tables.

Table B.1: *Critical values for the Dickey-Fuller test for a sample of 250 observations*

Test specification	10%	5%	1%
Regression with constant but no trend	-2.58	-2.88	-3.46
Regression with constant and trend	-3.13	-3.43	-3.99

Notes: Critical values are based on estimated OLS t-statistics

Source: Hamilton (1994)

I also need to choose how many lags to incorporate when I construct the AR equation, and here I have several approaches to choose from. One approach is to use automatic lag selectors such as Akaike information criterion (AIC) or Bayes information criterion (BIC). Another approach, proposed by Ng and Perron (1995), is to set a maximum lag length according to some maximum lag length selector, run the ADF test with this lag length and then use a t-test to check if the last lagged difference included is statistical significant different from zero. If it is significant, run ADF test with this lag length. If not, conduct the ADF test once more with one less lagged difference, (Stock and Watson, 2007). I will use the latter approach and use a maximum lag selector proposed by Schwert (2002):

$$p_{max} = 12\left(\frac{T}{100}\right)^{0.25}$$

The integer of p_{max} is the lag length and T is the number of observations. With 198 observations for most of my series, the integer of this equation corresponds to a maximum lag length of 14 for most of the series in the dataset. The maximum lag length will be specified in the unit root test statistics tables presented in this thesis.

B.2 Cointegration

We usually think about inference between multiple series when doing economics. Expanding the theory in section B.1, we have a concept called cointegration. This happens in cases where two variables drift in the same way or if it appears to be some sort of a long run relationship between the variables. Such long run relationships where two or more variables share the same type of stochastic drift could be implicated by economic theory. If a long-run relationship exists, we can have that a linear combination of these two variables are I(0) even if the two variables separately are I(1), since they follow the same trend. In other words, there exists a coefficient that makes the combination of these two variables to be I(0). Two series are therefore said to be cointegrated if they have a common stochastic trend following Hendry and Nielsen (2007).

This theory could of course be expanded to including multiple variables. Let $\boldsymbol{Y}_t$ be a $(n \times 1)$ vector of n different I(1) variables. If there exists a coefficient vector $\boldsymbol{\beta}$ such that $\boldsymbol{\beta}'\boldsymbol{Y}_t = \beta_1 Y_{1t} + \beta_2 Y_{2t} + .. + \beta_n Y_{nt} \sim$ I(0), then the vector $\boldsymbol{\beta}$ is called the a cointegrated vector according to Hamilton (1994). It can also exists more than one vector with the properties of $\boldsymbol{\beta}$. The number of cointegrated vectors is also called the cointegration rank. If there are k different linear combinations between the variables in $\boldsymbol{Y}_t$, then the cointegration rank will be k (Hendry and Nielsen, 2007).

Econometricians have several tests to choose from in their search for cointegration. It is normal to distinguish between two types of tests. The first set of tests could be applied in the case of at most one cointegrating vector between the variables included. The most widely used test in this category is called the Engle-Granger test and is a residual test based on Engle and Granger (1987).

The other types of tests are applied in the cases where we suspect more than one cointegrating vector. The preferred test here is called the Johansen test and is based on work by Søren Johansen. Engle-Grangers two step procedure will be briefly explained in this section while the Johansen approach will be the center of attention in appendix B.3.

The definition of cointegration as stated above were defined as, $\boldsymbol{\beta}'\boldsymbol{Y}_t \sim$I(0). However, this cointegration vector $\boldsymbol{\beta}'$ is not unique since any transformation with a nonzero scalar c would also be stationary; $c \cdot \boldsymbol{\beta}'\boldsymbol{Y}_t = \boldsymbol{\beta}^{*'}\boldsymbol{Y}_t \sim$ I(0). Hence, a normalization is often used, and a typical normalization is $\boldsymbol{\beta}^* = (1, -\beta_2, \ldots, -\beta_n)'$ so that

$$\boldsymbol{\beta}^{*'}\boldsymbol{Y}_t = Y_{1t} - \beta_2 Y_{2t} - \ldots - \beta_n Y_{nt} = \upsilon_t$$

or equivalently

$$Y_{1t} = \beta_2 Y_{2t} + \ldots + \beta_n Y_{nt} + \upsilon_t$$

Here $\upsilon_t$is the cointegrating residual and should in long run equilibrium be equal to 0. Since $\boldsymbol{\beta}^{*'}\boldsymbol{Y}_t$ ~I(0), υ_t also needs to be I(0) in order for $\boldsymbol{\beta}^{*'}$to be a cointegrating vector. Hence we could test the cointegrating residual for unit roots in order to check if we have a cointegrating vector, (Hamilton, 1994)

The first step[25] in Engle-Grangers two step procedure is therefore to estimate a regression for $\boldsymbol{\beta}^{*'}$, since it is unknown. Engle-Granger proposed to use least squares for this step. The second step is to test the residuals from this regression υ_t for unit roots by for example applying ADF test on the residuals. If the residuals are stationary, then we have a cointegration vector (Stock and Watson, 2007). Null hypothesis for this test is that we do not have cointegration. The critical values for the test depend on how we specify the least squares regression and how we specify the unit root test. This test is limited in the sense that it cannot test if there are more than one cointegrating vector even in the cases where we suspect more than one cointegrating vector. In situations with more than two $I(1)$ variables, this could often be the case. The correct test to use in such cases is the Johansen test which can detect more than one cointegrating relation.

B.3 Vector Error Correction Models and Johansen test

The Granger Representation Theorem which states that every cointegrating relationship can be represented by an error correction model (Engle and Granger, 1987). Johansen developed a

[25] It is not always necessary to estimate $\boldsymbol{\beta}^{*'}$. In situations where the cointegrating vector is known, we could apply this vector instead of estimating a vector (Stock and Watson, 2007).

test of cointegration based on error correction models by testing the rank of the coefficient in front of the lagged endogenous vector.

Starting out with a VAR(p), where p stand for number of lags included, we could write the VAR in vector notation in following fashion:

$$\boldsymbol{Y_t} = \sum_{i=1}^{p} \boldsymbol{\beta}_i \boldsymbol{Y}_{t-i} + \boldsymbol{\epsilon_t}$$

Here $\boldsymbol{Y_t}$ is a vector consisting of the n I(1) variables included and $\boldsymbol{\beta}_i$ is the coefficient matrices of lag number $i = 1, .. p$ to the vector. We could easily rewrite this VAR into at Vector Error Correction Model (VECM).

$$\boldsymbol{\Delta Y_t} = \boldsymbol{\Pi Y_{t-1}} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma_i \Delta Y_{t-i}} + \boldsymbol{\epsilon_t} \tag{B.1}$$

where we have that at $\boldsymbol{\Gamma_i} = -\sum_{\boldsymbol{j=i+1}}^{\boldsymbol{p}} \boldsymbol{\beta}_j$ and $\boldsymbol{\Pi} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{p}} \boldsymbol{\beta}_j - \boldsymbol{I_n}$.

In this VECM, we have that $\boldsymbol{\Delta Y_t}$ is $I(0)$ as well as all its lags. The only term that potentially can be $I(1)$ is the one of $\boldsymbol{\Pi Y_{t-1}}$. In order for $\boldsymbol{\Delta Y_t}$ to be $I(0)$, we must have a cointegrating relationship in $\boldsymbol{\Pi Y_{t-1}}$ so it is also $I(0)$, (Johansen 1988; Johansen 1995).

The Johansen approach of testing for cointegration is to test the rank of $\boldsymbol{\Pi}$. The rank of a matrix refers to the number of independent linear combinations in the matrix according to Sydsæter and Øksendal (2006). There are two cases two consider[26], both when $\boldsymbol{\Pi}$ is singular and we have reduced rank, rank($\boldsymbol{\Pi}$) <n.

The case where rank($\boldsymbol{\Pi}$)=0 implies that $\boldsymbol{\Pi}$=0, and we have a $(n \times n)$ matrix of 0`s. $\boldsymbol{\Pi Y_{t-1}}$ disappear and $\boldsymbol{\Delta Y_t}$ in equation B.1 becomes a normal VAR in first differences. In this case, we do not have any cointegrating vectors.

The case where 0<rank($\boldsymbol{\Pi}$)<n is the case where we have cointegrating vectors. If the rank($\boldsymbol{\Pi}$)=r<n it means that we have r linearly independent cointegrating vectors. Using elementary matrix algebra, we know that we can rewrite into a product of two matrices $\boldsymbol{\Pi} = \boldsymbol{\alpha\beta}'$ where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(n \times r)$ matrices with rank r. Rewriting it in this way allows us to interpret the effects of the regression in an easy way. The rows of $\boldsymbol{\beta}'$ are the cointegrating

[26] In the case when $\boldsymbol{\Pi}$ have full rank (rank=n), all elements of $\boldsymbol{Y_{t-1}} \sim I(0)$. The VAR is then stationary anyway and there is no room for cointegrating vectors.

vectors, the matrix gives us the combinations of coefficients that are needed in order for $\boldsymbol{\beta}'\boldsymbol{Y_{t-1}} \sim I(0)$. As mentioned in section 4.2, we could normalize this vector as the cointegration vector is non-unique, an often used variant is to normalize one of the coefficients to 1. The $\boldsymbol{\alpha}$ matrix contains coefficients that could be interpreted as equilibrium adjustment coefficients as they tell how variables adjust to the cointegrating vector (Hendry and Nielsen, 2007).

The Johansen test is based on testing of the eigenvalues since the rank of $\boldsymbol{\Pi}$ is equal to the number of non-zero eigenvalues of $\boldsymbol{\Pi}$. There are two types of statistics available for testing for cointegration rank. I will only explain the trace test as I am going to use this statistic when testing for multiple cointegrating vectors.

Trace statistic is given by:

$Johansen_{Trace} = -T \sum_{i=r+1}^{n} \ln(1 - \lambda_i)$

T is number of observations, λ_i is the eigenvalues sorted after their value in the following manner: $\lambda_1 > \lambda_2 > \cdots > \lambda_n$ as stated in Johansen (1988).

The procedure is done stepwise by testing for low rank values first and then higher rank values if the null hypothesis are rejected.

H_0: $rank(\boldsymbol{\Pi}) = r$ against H_1: $rank(\boldsymbol{\Pi}) > r$ where $r = 0,1, \dots n-1$ is the rank tested.

We always start by testing whether the rank is zero (null hypothesis) or if it is bigger than zero. The maximum amount of cointegrating vectors feasible with n I(1) variables is $n - 1$. If we have no cointegrating vectors at all, the eigenvalues should be close to zero and hence the trace statistic should be small since all $\ln(1 - \lambda)$ would be close to zero. Large test statistics leads us to rejection of the null hypothesis. If the null hypothesis cannot be rejected, we conclude that there are no cointegrating vectors. If we however reject the null hypothesis the first time, we proceed by testing for whether the matrix have rank 1 (null hypothesis) or if it have higher rank than 1. This sequential testing procedure continues we cannot dismiss the null hypothesis anymore and we have found the rank of the matrix. At each new test step, we drop out the largest eigenvalue included in the previous test step when testing (Johansen, 1995).

The critical values relevant for the trace test are tabulated in for example Johansen (1995). The critical values depend on how we specify the model. Johansen (1995) show five different model specifications and corresponding critical values.

B.4 Cointegration test results

Table B.2: *Johansen trace test for Portfolio Shift model*

Test specification: constant included in both VAR and cointegration equation

USD/CAD					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0617	17.4960	29.7971	0.6034
Rank=1	Rank≥2	0.0259	5.2742	15.4947	0.7790
USD/EUR					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0814	29.1441	29.7971	0.0593
Rank=1	Rank≥2	0.0654	12.9357	15.4947	0.1172
USD/GBP					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0969	30.9615	29.7971	0.0366
Rank=1	Rank≥2	0.0412	11.2939	15.4947	0.1941
USD/JPY					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.1585	39.725	29.7971	0.0026
Rank=1	Rank≥2	0.0325	6.4075	15.4947	0.6473

Test specification: constant included in VAR, constant and trend in cointegration equation

USD/CAD					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0672	24.7422	42.9152	0.8025
Rank=1	Rank≥2	0.0362	11.3849	25.8721	0.8523
USD/EUR					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0822	31.7204	42.9152	0.4036
Rank=1	Rank≥2	0.0727	15.3314	25.8721	0.5471
For USD/GBP					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.0976	32.5376	42.9152	0.3599
Rank=1	Rank≥2	0.0422	12.7151	25.8721	0.7601
USD/JPY					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.1653	43.7923	42.9152	0.0407
Rank=1	Rank≥2	0.0430	8.9277	25.8721	0.9624

Notes: p-values given in EViews are according to MacKinnon et al. (1999).

Table B.3: *Johansen trace test for Liquidity Shock model*

Test specification: constant included in both VAR and cointegration equation

USD/CAD					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.1957	111.8300	95.7537	0.0025
Rank=1	Rank≥2	0.1635	70.2363	69.8189	0.0463
Rank=2	Rank≥3	0.0856	36.1252	47.8561	0.3901
USD/EUR					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.2048	123.9811	95.7537	0.0002
Rank=1	Rank≥2	0.1672	85.4750	69.8189	0.0017
Rank=2	Rank≥3	0.1498	54.7401	47.8561	0.0099
Rank=3	Rank≥4	0.0957	27.4808	29.7971	0.0904
USD/GBP					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.3389	111.6378	95.7537	0.0026
Rank=1	Rank≥2	0.0841	32.1898	69.8189	0.9976
USD/JPY					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.3078	140.4815	95.7537	0.0000
Rank=1	Rank≥2	0.1699	70.2121	69.8189	0.0465
Rank=2	Rank≥3	0.1055	34.6458	47.8561	0.4668

Test specification: constant included in VAR, constant and trend in cointegration equation

USD/CAD					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.3174	157.8288	117.7082	0.0000
Rank=1	Rank≥2	0.1639	84.8905	88.8038	0.0927
USD/EUR					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.2579	163.7980	117.7082	0.0000
Rank=1	Rank≥2	0.1968	113.6774	88.8038	0.0003
Rank=2	Rank≥3	0.1622	76.8682	63.8761	0.0028
Rank=3	Rank≥4	0.1388	47.1370	42.9152	0.0179
Rank=4	Rank≥5	0.0813	22.0247	25.8721	0.1400
USD/GBP					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.3529	147.6956	117.7082	0.0002
Rank=1	Rank≥2	0.1733	64.1261	88.8038	0.7303
USD/JPY					
H_0	H_1	Eigenvalue	Trace statistic	5% Critical value	P-value
Rank=0	Rank≥1	0.3301	157.5988	117.7082	0.0000
Rank=1	Rank≥2	0.1699	81.0826	88.8038	0.1584

Notes: p-values given in EViews are according to MacKinnon et al. (1999).

C Regressions and test diagnostics

C.1 Basic theory of regression diagnostics

Jarque-Bera test for normality

The Jarque-Bera test is a test statistic for testing whether the series is normally distributed. In our regressions we have interest of testing whether our residuals are normal distributed as they should be according to theory. The test looks at the skewness and kurtosis of the series of consideration and measures this against those of a normal distribution (Jarque and Bera, 1980).

Test statistic is given by

$$Jarque - Bera\colon\ \frac{n}{6}\left(s^2 + \frac{(k-3)^2}{4}\right)$$

Here s is the skewness and k is the kurtosis of the series. Null hypothesis is that the series is normally distributed, and under the null hypothesis, the Jarque-Bera statitistic is chi-squared distributed with two degrees of freedom. High test statistics suggest that we can reject the null hypothesis of normal distribution. The reported p-value is the probability of rejecting the null hypothesis when it is in fact true (Kennedy, 2008).

Lagrange Multiplier test for autocorrelation

The Lagrange Multiplier test for serial correlation has the advantage compared to the Durbin-Watson test that it is applicable when there are lagged dependent variables included in the regression. The test is a residual-based test and we run a regression on the residuals from the original regression using p lag of the residuals and the dependent variables from the regression as dependent variables in the residual regression.

$$Y_t = \boldsymbol{X_t \beta} + \epsilon_t$$

$$\widehat{\epsilon_t} = \boldsymbol{X_t \xi} + \sum_{i=1}^{p} \alpha_i \, \widehat{\epsilon_{t-\iota}} + \upsilon_t$$

The Breusch-Godfrey test statistic is given by as number of observations in residual regression times the R-squared from this regression according to Greene (2008). This test statistic is asymptotically distributed as chi-squared with p degrees of freedom. Null hypothesis is null serial correlation in the residuals. High test statistics value leads us to rejection of the null hypothesis.

White test for heteroskedasticity

The White test for heteroskedasticity is done according to the original paper from White (1980). The test is based on a auxiliary regression on squared residuals. First step is to estimate the OLS of interest, and then retrieve the residuals from this regression.

$$Y_t = \beta_1 X_{1t} + \beta_2 X_{2t} + \epsilon_t$$

The test regression is then specified by taking a regression with the squared residuals on each explanatory variable, squared of each explanatory variable and the cross products of the explanatory variables.

$$\hat{\epsilon_t}^2 = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + \alpha_3 {X_{1t}}^2 + \alpha_4 {X_{2t}}^2 + \alpha_3 X_{1t} X_{2t} + \upsilon_t$$

The test statistic is given by R-squared multiplied with number of observations included in the auxiliary regression. Test statistic is asymptotically distributed as chi-squared with degrees of freedom equal to number of regressors included in the auxiliary regression. The test is specified with no heteroskedasticity as null hypothesis. A high test value would therefore indicate heteroskedasticity and lead us to rejection of the null hypothesis according to (Greene, 2008).

ARCH test for autoregressive conditional heteroskedasticity

This test based on Engle (1982) tests for autoregressive conditional heteroskedasticity (ARCH). The presence of ARCH effects does not invalidate OLS inference, but it may result in loss of efficiency. The test statistic is computed from an auxiliary test regression on the residuals.

$$\widehat{\epsilon_t}^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \widehat{\epsilon_{t-\iota}}^2 + \upsilon_t$$

Here p denotes the order of squared residuals included in the auxiliary regression. The statistic is defined as number of observations included times the R-squared from the auxiliary regression. The test statistic is asymptotically distributed as chi-squared with p degrees of freedom. Null hypothesis is null ARCH effects. High test values lead us to rejection of the null hypothesis (Hill et al., 2008).

C.2 Extra regressions

Table C.1: *Portfolio Shift model estimation output, model [5] – [7] with adjusted net option included separately*

Regressor	Dependent variable: Δlog(USD/CAD)			Dependent variable: Δlog(USD/EUR)		
	[5]	[6]	[7]	[5]	[6]	[7]
$Constant$	-0.1872 (0.1417)	-0.2143 (0.1376)	-0.1894 (0.1516)	0.0055 (0.2256)	-0.0994 (0.2714)	-0.0036 (0.2077)
$i^F - i^{USD}$		-0.1892 (0.1190)			-0.2475 (0.2155)	
$Adj. order\ flow$	-0.0174*** (0.0039)	-0.0175*** (0.0038)	-0.0176*** (0.0038)	-0.0051*** (0.0019)	-0.0051*** (0.0018)	-0.0050*** (0.0018)
$Adj. net\ option$	-0.0911*** (0.0289)	-0.0928*** (0.0270)	-0.0904** (0.0409)	-0.0019 (0.0195)	0.0005 (0.0203)	-0.0013 (0.0186)
$\Delta(i^F - i^{USD})$			-0.1489 (0.5278)			-0.6618 (0.5435)
Diagnostics						
Adjusted R2	0.2243	0.2273	0.2206	0.0284	0.0363	0.0275
Observations	193	193	193	195	195	195

Regressor	Dependent variable: Δlog(USD/GBP)			Dependent variable: Δlog(USD/JPY)		
	[5]	[6]	[7]	[5]	[6]	[7]
$Constant$	-0.0419 (0.1637)	0.0292 (0.1994)	-0.0641 (0.1511)	-0.0580 (0.2203)	-0.9325*** (0.3349)	-0.0542 (0.2112)
$i^F - i^{USD}$		-0.0635 (0.1663)			-0.2481** (0.0980)	
$Adj. order\ flow$	-0.0120*** (0.0036)	-0.0119*** (0.0035)	-0.0151*** (0.0037)	-0.1129** (0.0525)	-0.1189** (0.0516)	-0.1173** (0.0498)
$Adj. net\ option$	-0.0661** (0.0281)	-0.0682*** (0.0260)	-0.0832*** (0.0279)	-0.2271*** (0.0723)	-0.2305*** (0.0622)	-0.1948*** (0.0590)
$\Delta(i^F - i^{USD})$			-1.7136*** (0.3524)			-1.2242 (0.8768)
Diagnostics						
Adjusted R2	0.0766	0.0726	0.1212	0.0693	0.0851	0.0776
Observations	195	195	195	193	193	193

Remarks: All estimated coefficients and standard errors are multiplied with 100. HAC standard errors are given in brackets. Estimation sample: January 1994 – June 2010.
***, **, * indicates significance at 1% level, 5% level and 10% level

Table C.2: *Dynamic OLS (DOLS) estimation results of cointegration relationship for USD/JPY*[a]

	USD/JPY
Interest diff	-1.3347 (1.0221)
Cumulative adjusted net flow	-0.1246* (0.0691)
Money diff	1.8037*** (0.3591)
IPR diff	0.3914 (0.4448)
CPI diff	-2.6028* (1.5429)
Trend	0.4322 (0.3856)
C	457.4815

[a] Dependent variable: Δlog(USD/JPY).
Notes: Dynamic OLS with number of leads and lags decided by BIC, max number of lags are set to 12. All coefficients and standard errors are scaled by 100. HAC standard errors are given in brackets. Estimation sample: January 1994 – June 2010.
***, **, * indicates significance at 1% level, 5% level and 10% level.

C.3 Regression diagnostics

Table C.3: *Regression diagnostics for model [1]-[4]*

	For USD/CAD regressions				For USD/EUR regressions			
Diagnostics	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Jarque-Bera	1295.3690 [0.0000]	454.4740 [0.0000]	475.3232 [0.0000]	446.7307 [0.0000]	31.3128 [0.0000]	21.8405 [0.0000]	37.1388 [0.0000]	33.2202 [0.0000]
LM test(2)[a]	0.1250 [0.9394]	0.0022 [0.9989]	0.0110 [0.9945]	0.0589 [0.9710]	1.5528 [0.4601]	0.9754 [0.6140]	1.3069 [0.5203]	0.9742 [0.6144]
White test	1.8267 [0.4012]	88.2550 [0.0000]	98.7526 [0.0000]	91.0412 [0.0000]	3.9346 [0.1398]	0.8903 [0.6407]	6.2487 [0.2828]	28.6687 [0.0000]
ARCH test	0.0219 [0.8824]	0.0306 [0.8612]	0.0203 [0.8866]	0.0911 [0.7628]	0.1716 [0.6787]	0.2786 [0.5976]	0.2019 [0.6532]	0.4825 [0.4873]
Observations	197	197	197	197	197	197	197	197

	For USD/CAD regressions				For USD/EUR regressions			
Diagnostics	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Jarque-Bera	65.8366 [0.0000]	62.6827 [0.0000]	63.0219 [0.0000]	118.9817 [0.0000]	68.2397 [0.0000]	27.8060 [0.0000]	34.4430 [0.0000]	25.0090 [0.0000]
LM test(2)[a]	0.9068 [0.6355]	0.8842 [0.6427]	0.8883 [0.6414]	0.7566 [0.6850]	0.8401 [0.6570]	0.8350 [0.6587]	0.4915 [0.7821]	1.2090 [0.5463]
White test	5.8689 [0.0532]	74.9692 [0.0000]	80.9077 [0.0000]	125.6585 [0.0000]	0.1774 [0.9151]	14.2668 [0.0008]	16.8421 [0.0048]	20.3439 [0.0011]
ARCH test	4.2957 [0.0382]	4.3380 [0.0373]	4.3269 [0.0375]	0.6896 [0.4063]	0.1617 [0.6876]	0.0107 [0.9176]	0.0323 [0.8575]	0.0012 [0.9724]
Observations	197	197	197	197	197	197	197	197

[a] Lagrange Multiplier test for autocorrelation of order 2.

Notes: p-values for respective tests are given in square brackets. The null is rejected if p-value is lower than 0.05.

Table C.4: *Regression diagnostics for model [2-2]-[4-2]*

	For USD/CAD regressions			For USD/EUR regressions		
Diagnostics	[2-2]	[3-2]	[4-2]	[2-2]	[3-2]	[4-2]
Jarque-Bera	6.0600 [0.0483]	6.8370 [0.0328]	6.1410 [0.0464]	14.1337 [0.0009]	23.0771 [0.0000]	22.7700 [0.0000]
LM test(2)[a]	0.8593 [0.6507]	0.9539 [0.6207]	0.8964 [0.6388]	0.8404 [0.6569]	1.0446 [0.5931]	0.7985 [0.6708]
White test	9.7192 [0.0078]	14.9778 [0.0105]	11.1639 [0.0482]	13.0199 [0.0015]	22.9720 [0.0003]	38.0938 [0.0000]
ARCH test	15.2975 [0.0001]	13.9195 [0.0002]	15.3363 [0.0001]	0.2145 [0.6433]	0.1580 [0.6910]	0.4566 [0.4992]
Observations	195	195	195	193	193	193

	For USD/GBP regressions			For USD/JPY regressions		
Diagnostics	[2-2]	[3-2]	[4-2]	[2-2]	[3-2]	[4-2]
Jarque-Bera	5.6656 [0.0588]	5.6384 [0.0597]	4.1456 [0.1258]	24.1289 [0.0000]	28.3701 [0.0000]	23.1478 [0.0000]
LM test(2)[a]	0.1828 [0.9126]	0.1835 [0.9123]	0.5364 [0.7648]	0.6594 [0.7192]	0.3104 [0.8562]	0.8623 [0.6498]
White test	3.4502 [0.1782]	26.1651 [0.0001]	22.6241 [0.0004]	15.5328 [0.0004]	17.7151 [0.0033]	22.5919 [0.0004]
ARCH test	0.0429 [0.8360]	0.0422 [0.8372]	0.7570 [0.3843]	0.0403 [0.8409]	0.0240 [0.8770]	0.0642 [0.8000]
Observations	195	195	195	193	193	193

[a] Lagrange Multiplier test for autocorrelation of order 2.

Notes: p-values for respective tests are given in square brackets. The null is rejected if p-value is lower than 0.05.

Table C.5: *Regression diagnostics for model [5]-[7]*

	For USD/CAD regressions			**For USD/EUR regressions**		
Diagnostics	[5]	[6]	[7]	[5]	[6]	[7]
Jarque-Bera	5.0262 [0.0810]	5.6831 [0.0583]	5.1324 [0.0768]	13.8973 [0.0010]	21.9657 [0.0000]	20.7336 [0.0000]
LM test(2)[a]	0.7381 [0.6914]	0.8432 [0.6560]	0.7796 [0.6772]	0.8560 [0.6518]	1.0983 [0.5775]	0.8226 [0.6628]
White test	6.0948 [0.0475]	11.1769 [0.0480]	7.9142 [0.1610]	19.7108 [0.0001]	33.4114 [0.0000]	45.0995 [0.0000]
ARCH test	14.7419 [0.0001]	13.3418 [0.0003]	14.7857 [0.0001]	0.3082 [0.5788]	0.2615 [0.6091]	0.5167 [0.4723]
Observations	196	196	196	195	195	195

	For USD/GBP regressions			**For USD/JPY regressions**		
Diagnostics	[5]	[6]	[7]	[5]	[6]	[7]
Jarque-Bera	6.0731 [0.0480]	6.1496 [0.0462]	3.2847 [0.1935]	17.0126 [0.0002]	22.5025 [0.0000]	20.8302 [0.0000]
LM test(2)[a]	0.2058 [0.9022]	0.2048 [0.9027]	0.7888 [0.6741]	0.4111 [0.8142]	0.1028 [0.9499]	0.7303 [0.6941]
White test	5.2701 [0.0717]	18.5158 [0.0024]	18.7174 [0.0022]	6.6915 [0.0352]	6.7336 [0.2412]	9.0081 [0.1087]
ARCH test	0.1232 [0.7256]	0.1270 [0.7216]	1.6116 [0.2043]	0.0026 [0.9592]	0.0241 [0.8766]	0.0003 [0.9860]
Observations	197	197	197	197	197	197

[a] Lagrange Multiplier test for autocorrelation of order 2.

Notes: p-values for respective tests are given in square brackets. The null is rejected if p-value is lower than 0.05.

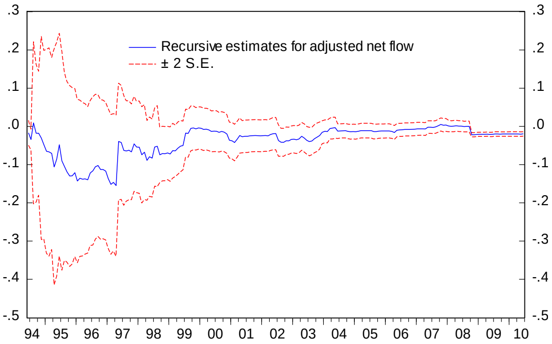


Figure C.1 a: Adjusted net flow, CAD

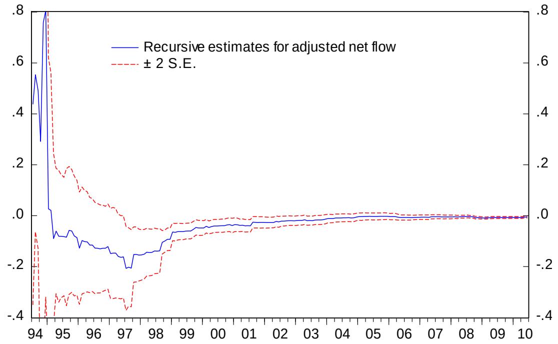


Figure C.1 b: Adjusted net flow, EUR

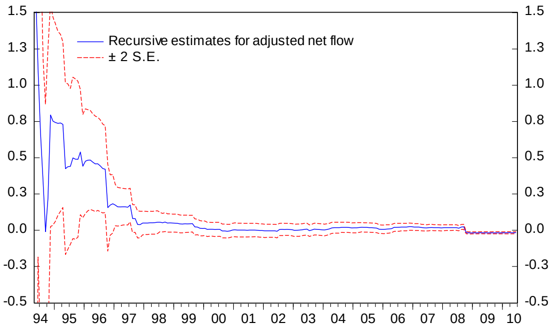


Figure C.1 c: Adjusted net flow, GBP

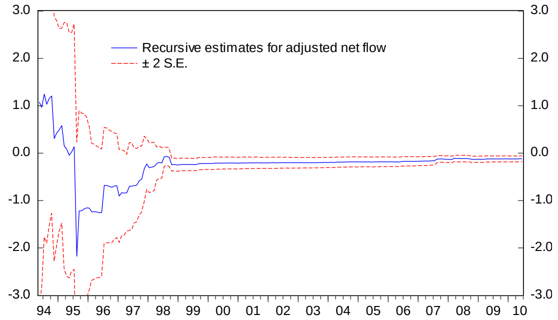


Figure C.1 d: Adjusted net flow, JPY

Figure C.1: *Recursive estimates of adjusted net flow in model [7]. January 1994 – June 2010.*

D Derivations

D.1 Liquidity Shock model

The Liquidity Shock model presented in Chinn and Moore (2010) consists of a CES utility function:

$$E_0 = \sum_{t=0}^{\infty} \delta^t \frac{\left[\left[C_t^j\right]^{\frac{\theta-1}{\theta}} + e^{\frac{\eta^j}{\theta}} \left[\frac{M_t^j}{P_t^j}\right]^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}}{\frac{\theta}{\theta-1}} \quad j = H, F$$

a budget equation, defined as: $W_t^j = P_t^j C_t^j + M_t^j + \frac{B_t^j}{1+i_t^j}$ (D.1)

while the wealth is evolving according to: $W_{t+1}^j = P_{t+1}^j Y_{t+1}^j + B_t^j + M_t^j$ (D.2)

W_t^j is the state variable while C_t^j, M_t^j and B_t^j are the control variables. Solving for C_t^j from (D.1), I get that

$$C_t^j = \frac{1}{P_t^j}\left(W_t^j - M_t^j - \frac{B_t^j}{1+i_t^j}\right) \tag{D.3}$$

Lagging the expression (D.2) one period and inserting for W_t^j into (D.3) I get:

$$C_t^j = Y_t^j + \frac{1}{P_t^j}\left(M_{t-1}^j + B_{t-1}^j - M_t^j - \frac{B_t^j}{1+i_t^j}\right)$$

Inserting for C_t^j into the utility function, I am able now maximize with respect to B_t^j and M_t^j. After some algebra manipulation I get that first order conditions can be written as:

$$FOC_{M_t^j}: \; u'_{C_t^j}(\cdot)\left[\frac{1}{P_t^j} e^{\frac{\eta_t^j}{\theta}} \left(\frac{M_t^j}{P_t^j}\right)^{-\frac{1}{\theta}} - \frac{{C_t^j}^{-\frac{1}{\theta}}}{P_t^j}\right] + \sigma\, u'_{C_{t+1}^j}(\cdot)\left[\frac{{C_{t+1}^j}^{-\frac{1}{\theta}}}{P_{t+1}^j}\right] = 0 \tag{D.4}$$

$$FOC_{B_t^j}: \; u'_{C_t^j}(\cdot)\left[\frac{-{C_t^j}^{-\frac{1}{\theta}}}{(1+i)P_t^j}\right] + \sigma\, u'_{C_{t+1}^j}(\cdot)\left[\frac{{C_{t+1}^j}^{-\frac{1}{\theta}}}{P_{t+1}^j}\right] = 0 \tag{D.5}$$

Using that the last term in both first order conditions are identical, I find be removing these two terms that:

$$\left[\frac{1}{P_t^j} e^{\frac{\eta_t^j}{\theta}} \left(\frac{M_t^j}{P_t^j}\right)^{-\frac{1}{\theta}} - \frac{C_t^{j^{-\frac{1}{\theta}}}}{P_t^j}\right] = \left[\frac{-C_t^{j^{-\frac{1}{\theta}}}}{(1+i)P_t^j}\right]$$

$$\left[e^{\frac{\eta_t^j}{\theta}} \left(\frac{M_t^j}{P_t^j}\right)^{-\frac{1}{\theta}} - C_t^{j^{-\frac{1}{\theta}}}\right] = \left[\frac{-C_t^{j^{-\frac{1}{\theta}}}}{(1+i)}\right]$$

$$e^{\frac{\eta_t^j}{\theta}} \left(\frac{M_t^j}{P_t^j}\right)^{-\frac{1}{\theta}} = \frac{i}{1+i} C_t^{j^{-\frac{1}{\theta}}}$$

Taking natural log of this expression I find that

$$\frac{\eta_t^j}{\theta} - \frac{1}{\theta}\left(lnM_t^j - lnP_t^j\right) = ln\left(\frac{i}{1+i}\right) - \frac{1}{\theta} lnC_t^j \tag{D.6}$$

Using lowercase to denote the natural log of a variable and writing $ln\left(\frac{i}{1+i}\right) = r_t^j$, I get a demand function for money:

$$m_t^j = p_t^j + c_t^j + \eta_t^j + \theta r_t^j \tag{D.7}$$

Defining Purchasing Power Parity (PPP) as $s_t = p_t^H - p_t^F$ and inserting for p_t^H and p_t^F into (D.7), I get expression (5).