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Forecasting exchange rate returns and transaction costs

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Forecasting exchange rate returns and transaction costs

Abstract

Order flow in interdealer FX markets is driven by large banks, which are viewed as more informed (Bjønnes, Osler & Rime, 2011). Order flow is a key determinant of exchange rates and bid-ask spreads, because order flow conveys information that is assumed to be related to future exchange rate fundamentals. Thus, the impact of order flow on exchange rates is persistent at short to medium horizons regardless of the source of exchange rate fluctuation, because agents (i.e. dealers) rationally interpret the resulting exchange rate movement as information about future exchange rate fundamentals. The persistent impact of order flow on exchange rates and bid-ask spreads implies that order flow should provide forecasting power for both future exchange rates and future bid-ask spreads.

This also implies that order flow specification should improve returns, forecasting accuracy and performance stability under market volatility relative to naïve forecasting models. This is due to the order flow model being based on information about future exchange rate fundamentals, whereas naïve forecasting models are only based on information about either past or present information on exchange rate fundamentals.

This paper examines the forecasting ability of order flow for both future exchange rates and future bid-ask spreads, using 13 currency pairs that include the heavily traded Euro, the Great Britain pound and the Australian dollar. This paper then evaluates returns, forecasting accuracy and performance stability under market volatility by comparing the results of the order flow model with those of three alternative naïve forecasting models: (1) A buy-and-hold strategy; (2) a naïve random walk model; and (3) a moving average model. This paper shows that order flow has superior forecasting ability in terms of generating higher returns, lower bid-ask spreads, and producing more stable and less volatile performance. In addition, this paper also provides evidence of an intraday pattern of bid-ask spreads that suggests periods at which bid-ask spreads are narrower, during which trading costs can be minimised.

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1. Introduction

The Foreign Exchange (FX) market is highly liquid and economically important. According to BIS (2010), the FX market turns over \$US4 trillion each day in volume, making it the largest financial market in the world.

Given this high daily turnover in FX markets, a higher portfolio turnover rate may indicate a higher transaction cost for active portfolio managers, as well as for dealers. Therefore, traders are not only concerned with positive returns, but also with transaction costs (i.e. bid-ask spreads), as it is established fact that lower trading costs generate higher returns. Thus, forecasting exchange rates as well as trading cost (i.e. bid-ask spread) is a significant component of active portfolio managers' skill.

Order flow in the interdealer FX market is driven by large banks, which are viewed as more informed (Bjønnes, Osler & Rime, 2011). Order flow is a key determinant of exchange rates and bid-ask spreads, because order flow conveys information that is assumed to be related to future exchange rate fundamentals. Thus, the impact of order flow on exchange rates is persistent at short to medium horizons regardless of the source of exchange rate fluctuation, as agents (i.e. dealers) rationally interpret the resulting exchange rate movement as information about future exchange rate fundamentals.

Order flow conveys information about future exchange rate fundamentals (Glosten & Milgrom, 1985) and, thus, a sophisticated forecasting model based on order flow should outperform naïve forecasting models that are only based on past, or present, information about exchange rate fundamentals.

Therefore, my objective is to examine the forecasting ability of order flow, and then evaluate the forecasting performance of the order flow model relative to naïve forecasting models for future exchange rate returns and future bid-ask spreads at short to medium horizons (ranging from 30-minutes to one week).

I use 13 currency pairs including the Euro and the Great Britain pound, which have been widely featured in the literature. I extend the extant literature by introducing the following 11 currency pairs; United Arab Emirates Dirham (AED/USD), Australian dollar (AUD/USD), Bahraini Dina (BHD/USD), Chinese Yuan (CNY/USD), Hungarian Forint (HUF/USD) , Israeli Shekel (ILS/USD), Korean won (KWD/USD), Norwegian Krone(NOK/USD), Polish Zloty (PLN/USD), Romanian New Leu (RON/USD), and South African rand (ZAR/USD).

In this paper, I extend the earlier results of Messe and Rogoff (1983) and Evan and Lyons (2005), who only consider the forecasting accuracy of the order flow model, by introducing the performance stability of forecasting models under market volatility. I evaluate the forecasting performance of the order flow model in three ways in terms of: (1) Generating returns, (2) forecasting accuracy, and (3) performance stability under market volatility. Furthermore, I extend the earliest study by introducing more benchmark models, which I shall use in forecasting comparisons: (1) The benchmark naïve random walk model, as in Messe and Rogoff (1983) and Evan and Lyons (2005); (2) a passive trading strategy, a buy-and-hold model; and (3) a less sophisticated forecasting model, a moving average model.

My data derives from transaction-level information obtained from the Thomson Reuters database, which provides approximately 16 years of data for the Australian, Great Britain and South African currency pairs, 14 years of data for the Euro, Israeli and Poland currency pairs, 12 years of data for the Hungary and Norway currency pairs, 8 years of data for the Romanian currency pair, 3 years of data for the UAE, Bahrain and Korean currency pairs, and 1 year of data for the Chinese currency pairs. The sample starts in 1997 and ends in 2013.

My analysis consists of four sets of empirical exercises.

First, I examine whether the impact of order flow itself is persistent at 30 minutes. Bacchetta and Wincoop (2006) argue that the impact of order flow is persistent at a short to medium horizon and, consistent with that finding, I find that the impact of order flow is significantly persistent at the 30-minute time horizon.

Second, I examine how order flow is contemporaneously related to change in exchange rates and bid-ask spread before I examine the persistent impact of lagged order flow on both future exchange rate returns and future bid-ask spread at short to medium horizons. The relevant theory is information theory, developed by Glosten and Milgrom (1985), which predicts that order flow is contemporaneously positively related to change in both exchange rates and the bid-ask spread. Consistent with Glosten and Milgrom (1985), I find that order flow is contemporaneously positively related to changes in exchange rates. Contrary to Glosten and Milgrom (1985), however, I find that order flow is contemporaneously negatively related to bid-ask spread.

Third, I examine the forecasting ability of order flow for future bid-ask spread. Consistent with Bacchetta and Wincoop (2006), I find that future bid-ask spread is significantly related to the lagged order flow, providing evidence that the impact of order flow is persistent at short to medium horizons.

Fourth, I examine the intraday pattern of currency bid-ask spread. Consistent with Adamati and Pflleiderer (1988), who argue that there is an intraday pattern in trading volume and bid-ask spreads, I find an intraday pattern in bid-ask spreads. I use the results later, when developing the moving average model.

Finally, I compare the forecasting performance of the order flow model against three naïve forecasting models: (1) The buy-and-hold strategy; (2) the naïve random walk and; (3) the moving average model: in terms of generating returns, forecasting accuracy and performance stability under market volatility. Consistent with the implication of this paper that the order flow model should provide higher returns, lower forecasting errors, and more stable and less volatile performance than the naïve forecasting models; due to the fact that the order flow model is based on information about future exchange rate fundamentals whereas all naïve forecasting models are based on past, or present information about fundamentals; I find that that order flow provides superior performance in all three evaluations relative to the naïve forecasting models.

The contribution of this paper to the literature is that I use currency pairs that have not been featured in the previous literature. I also contribute several other aspects to the literature. First, I present intraday patterns of bid-ask spreads for currency pairs that have not been featured in the previous studies, as well as presenting the existence of an intraday pattern in currency bid-ask spreads at a shorter horizon: The 30-minute time horizon. Second, I show that the order flow strategy generates higher returns than the buy-and-hold strategy at a 1-week horizon and I provide break-even transaction costs to cover trading costs. Third, I introduce the performance stability of forecasting models under market volatility, which has not been featured in the previous literature in evaluating the forecasting ability of forecasting models.

The remainder of the paper is structured as follows: Section 2 presents the literature review and hypotheses. Section 3 outlines the data source and provides the description of the data. Section 4 presents the models. Section 5 reports the empirical results. Section 6 provides conclusions. Section 7 presents the references.

2. Literature Review and Hypothesis

In Foreign Exchange (FX) markets, information on macroeconomic exchange rate fundamentals (e.g. interest rates, inflation) are publicly announced (Meese & Rogoff, 1983). Some well-known early studies of exchange rate determination attempt to use these macroeconomic fundamentals to explain exchange rate fluctuation (Mark, 1995; Meese, 1990; Meese & Rogoff, 1983). Meese and Rogoff (1983), in particular, find that macroeconomic exchange rate fundamentals have weak explanatory power for exchange rate fluctuation over short to medium horizons (i.e. one to twelve-month horizons for 1970s US dollar/German Mark, US dollar/Great Britain pound and US Dollar/Japanese yen). Meese and Rogoff (1993) also examine the forecasting ability of macro-based exchange rate models relative to the naïve random walk model, and report a negative result: The benchmark random walk outperforms (not underperforms) the macro-based exchange rate models in forecasting ability. At longer horizons, however, (i.e. twelve to sixteen quarter horizons), Mark (1995) finds that macroeconomic exchange rate fundamentals have increasing explanatory power for exchange rate fluctuation. These mixed results suggest that, at short to medium horizons, exchange rates fluctuate in an unpredictable way, but in the long term, exchange rate fundamentals become relevant and determine exchange rates.

In the next sub-sections of the literature review, I present four hypotheses. For the first hypothesis, I discuss the theory and the empirical evidence from the literature to determine why order flow should provide forecasting power for future exchange rate returns and future currency bid-ask spreads, as well as why the order flow model should outperform naïve forecasting models in its forecasting ability. Next, I provide two hypotheses to complement the first hypothesis and each other. Finally, I discuss a hypothesis of intraday patterns of bid-ask spreads that suggests some periods, at which bid-ask spreads are narrower, allow for trading costs to be minimised.

H1: Order flow has forecasting power for future exchange rate returns and future currency bid-ask spreads

In this section, I discuss a theory and empirical evidence from the literature to demonstrate why order flow should provide forecasting power for future exchange rate returns and future currency bid-ask spreads, as well as why the order flow model should outperform naïve forecasting models in its forecasting ability.

Order flow is defined as buyer-initiated trades less seller-initiated trades (Evans & Lyons, 2002).

There is abundant evidence that order flow has strong explanatory power for exchange rate fluctuation at short to medium horizons (Bjønnes et al., 2011; Carlson & Lo, 2006; Carpenter & Wang, 2003; Evans & Lyons 2002; Evans & Lyons, 2005; Evans & Lyons, 2008; Frömmel, Mende & Menkhoff, 2008; Froot, O'Connell & Seasholes, 2001; Love & Payne, 2008; Lyons, 1995).

As stated above, unlike on the New York Stock Exchange (NYSE), all exchange rates' fundamental information is publicly announced in the FX markets, and it is uncommon for an agent to exploit unreleased private information about exchange rate fundamentals.

This implies that information heterogeneity across agents can play an important role in explaining the short to medium horizons exchange rate fluctuation.

The source of heterogeneity is informational; that is, some agents are assumed to be better informed about the future price of an asset than others (Admati & Pfleiderer, 1988; Bacchetta & Wincoop, 2006; Glosten & Milgrom, 1985; Kyle, 1985; Rime, Sarno & Sojli, 2010). A number of studies provide evidence supporting the heterogeneity belief on exchange rate determinants across market participants (Dunne, Hau & Moore, 2010; MacDonald & Marsh, 1996), and the role of order flow for revealing the information of informed agents (Bjønnes et al., 2011; Carlson & Lo, 2006; Carpenter & Wang, 2003; Evans & Lyons 2002; Evans & Lyons, 2005; Evans

& Lyons, 2008; Frömmel et al., 2008; Froot et al., 2001; Love & Payne, 2008; Lyons, 1995).

Studies find that publicly announced information on macroeconomic exchange rate fundamentals is impounded directly into the price as in a macro-based exchange rate model (Meese & Rogoff, 1983), or impounded indirectly via order flow (Carlson & Lo, 2006; Evans & Lyons 2002; Evans & Lyons, 2005; Evans & Lyons, 2008; Love & Payne, 2008), supporting information heterogeneity across agents and the role of order flow in revealing it.

Empirical evidence shows that between half and two-thirds of price relevant macro-news operates through order flow at short to medium horizons (Evans & Lyons, 2002; Love & Payne 2008; Rime et al., 2010).

Bacchetta and Wincoop (2006) provide scapegoat theory (person with mistakes) to explain why the impact of order flow on exchange rates can be persistent regardless of the source of exchange rate fluctuation at short to medium horizons. Note that there are two types of information heterogeneity: (1) Dispersed information about fundamentals; and (2) non-fundamental based heterogeneity (i.e. non-fundamental trades are motivated by liquidity and inventory concerns). Bacchetta and Wincoop (2006) argue that the impact of order flow can be persistent over short to medium horizons because agents rationally (and heterogeneously) interpret the resulting exchange rate movement as information about future exchange rate fundamentals at short to medium horizons. Thus, even in the case of non-fundamental trades, the impact can be persistent over short to medium horizons, as agents rationally misinterpret the resulting exchange rate movement as being information about future exchange rate fundamentals.

Froot and Ramadorai (2002), for example, show that it takes up to 70 days for the full impact of a shock to order flow to be incorporated into price. Berger, Chaboud, Chernenko, Howorka and Wright (2008) also examine the impact of order flow on US dollar/Japanese yen, using frequencies ranging from intradaily to monthly, with data spanning from January 1999 to December 2004. Consistent with the prediction of Bacchetta and Wincoop (2006), Berger et al. (2008) find that, although the impact of

order flow declines gradually over the longer horizon, the impact remains statistically and economically significant even at three months. Daniélsson, Payne and Luo (2002) show that order flow can be forecasted with own lags, while Osler, Mende and Menkho (2011) report that price continues moving in the direction implied by the information even after the first dealer (who is viewed as informed) has traded. Supporting the results of Daniélsson et al. (2002) and Osler et al. (2011), King, Osler and Rime (2012b) also show that uninformed dealers reverse the direction of their trades, so that this matches the direction of dealers who are viewed as more informed.

Due to the width of bid-ask spreads varying with the size of order flow, order flow also has a persistent impact on bid-ask spreads at short to medium horizons (Huang & Masulis, 1999). Menkhoff and Schmeling (2010) conclude that order flow is driven by informed traders. Thus, in interdealer FX markets, order flow is driven by large banks, which are viewed as more informed due to their large customer base (Bjønnes et al., 2011). Huang and Masulis (1999), for example, show that when a significant number of large banks are in the interdealer FX market, they display more aggressive pricing of liquidity services to attract customers, while other, smaller, banks that are interested in offering liquidity service later adjust the width of their bid-ask spread, so that it matches that of the larger banks.

This implies that the impact of order flow is persistent over short to medium horizons and, thus, order flow should provide forecasting power for future exchange rate returns and future currency bid-ask spreads.

This also implies that order flow specification should improve returns, forecasting accuracy and performance stability under market volatility, relative to naïve forecasting models, because the order flow model is based on information about future exchange rate fundamentals, whereas naïve forecasting models are only based on information about past or present information on exchange rate fundamentals.

Next, I provide two hypotheses to complement this hypothesis: The first concerns how order flow is contemporaneously related to change in exchange rates; and the

second concerns how order flow is contemporaneously related to the bid-ask spread.

H1.1: Exchange rate return is contemporaneously positively related to order flows

In this section, I discuss how order flow is contemporaneously related to changes in exchange rates.

The relevant theory is (asymmetry) information theory developed by Glosten and Milgrom (1985). The information theory emerges when dealers adjust prices in response to order flow that may convey private information about future price determinants. The source of the information asymmetry is informational; some agents are assumed to be better informed about future asset prices than others (Admati & Pfleiderer, 1988; Glosten & Milgrom, 1985; Kyle, 1985). On an empirical level, such informational asymmetry has two important implications. First, transaction activity (i.e. order flow) carries information and, thus, dealers adjust prices in response to order flow. This implies that buyer-initiated trades push up prices and seller-initiated trades push down prices. Second, uninformed dealers widen the bid-ask spread to protect themselves from adverse selection when faced with the possibility of trading with informed traders.

This section concerns the first implication; that order flow conveys information and dealers adjust prices in response to order flow.

Consistent with the information theory that some agents are more informed than others, studies have concluded that among customer types, financial customers; such as hedge funds, pension funds, and broker-dealers; are better informed than non-financial customers; such as corporate customers; who typically engage in international trade (i.e. imports and exports), because financial customers' trades anticipate upcoming returns (Bjønnes et al., 2011; Carpenter & Wang, 2003; Frömmelet et al., 2008; Froot et al., 2001).

As stated above, empirical evidence shows that between half and two-thirds of price

relevant macro-news operates through order flow, supporting the premise that order flow conveys information about dispersed information on future exchange rate fundamentals (Carlson & Lo, 2006; Evans & Lyons, 2002; Evans & Lyons, 2005; Evans & Lyons, 2008; Love & Payne, 2008).

Evans and Lyons (2002), for example, find that daily order flow explains an astonishing 60% of daily exchange rate returns of German mark/US dollar exchange rates, using data from Thomson Reuters, covering a period of four months from May to August, 1996. They also find that order flow related to non-fundamentals accounts for over half of the 60% variation,

Thus, this implies that exchange rate returns are contemporaneously positively related to order flows.

H1.2: Currency bid-ask spread is contemporaneously positively related to order flow

In this section, I discuss how order flow is contemporaneously related to bid-ask spread. This section concerns the second implication that uninformed dealers widen the bid-ask spread to protect themselves from adverse selection when faced with the possibility of trading with informed traders.

Order flow is a proxy for private information and larger trades are more likely to be undertaken by privately informed traders. This implies that bid-ask spread should be positively related to order flow; wider bid-ask spreads for larger trades. The additional widening of the bid-ask spread is referred to as the adverse selection component of the bid-ask spread.

The adverse selection theory has successfully explained the behaviour of bid-ask spreads on the NYSE: NYSE bid-ask spreads are wider for larger trades¹, indicating that NYSE dealers are risk-averse. As the NYSE has been extensively and widely studied, the stock market has provided inspiration for researchers to attempt to apply

¹ For example, Harris and Hasbrouck (1996), Peterson and Sirri (2003).

the adverse selection model to other financial markets to explain the behaviour of bid-ask spreads.

Studies of the behaviour of currency bid-ask spreads, however, provide no evidence of the adverse selection effect on the currency spread (King, Osler & Rime, 2012a; King et al., 2012b; Naik, Neuberger & Viswanathan, 1999; Osler, Mende & Menkho, 2004; Osler et al., 2011; Ramadorai, 2008). The empirical evidence shows that the pattern of bid-ask spread in FX markets is the opposite of that predicted by adverse selection; currency bid-ask spreads are narrower, not wider, for larger trades, or for informed trades. Osler et al. (2011), for example, attempt to apply the adverse selection model to explain the behaviour of the Euro/US dollar bid-ask spread over the 87 trading days from July 11, 2001 to November 9, 2001 for more informed customers; such as financial customers and customers making bigger trades; and find the opposite of that predicted by adverse selection. That is, they find that bid-ask spreads for informed trades and larger trades are narrower, not wider and that bid-ask spreads for uninformed trades and smaller traders are wider, not narrower. This indicates that adverse selection does not dominate the determination of currency bid-ask spreads.

The literatures emphasises the importance of market structure in explaining the contrasting findings of the bid-ask spread behaviour of two markets. Bjønnes et al. (2011) explain that, in two-tier FX markets, dealers who trade with informed customers can exploit the information when trading with other dealers in the interdealer FX market, whereas in the one-tier NYSE, dealers have no one else with whom to trade after observing an informed customer trade. Therefore, FX dealers have strong incentives to maximise their trading with informed customers then avoid them (McGroarty, ap Gwilym & Thomas, 2009; Naik et al., 1999; Osler et al., 2004), given that customer-dealer trades are only observed by two transacting parties (Bjønnes & Rime, 2005).

It must also be noted that greater transparency reduces adverse selection and also encourages uninformed traders to participate, thereby increasing market liquidity (Naik et al., 1999). The introduction of electronic systems in interdealer FX markets

in the early 1990s has enhanced market transparency and, thus, has reduced adverse selection, thereby reducing the (adverse selection component of) bid-ask spread. In the absence of adverse selection, the relation between trade volume and the bid-ask spread is negative, as suggested by Adamati and Pfleiderer (1988), because of strategic intraday pattern of trades by discretionary liquidity traders and informed traders. In interdealer FX markets, the competition between dealers is intense, particularly so during domestic trading hours, during which dealers strategically quote narrower bid-ask spreads to trade with informed customers (Ito & Hashimoto, 2006; McGroarty et al., 2009; Rinaldo, 2009).

This implies that, in the absence of adverse selection, currency bid-ask spread is negatively (not positively) related to contemporaneous order flow.

H2: The existence of intraday patterns in currency bid-ask spread

In this section, I discuss a hypothesis regarding intraday patterns in currency bid-ask spread that suggests periods during which bid-ask spreads are narrower and wider.

High frequency data is also used to examine the intraday pattern of trading volumes (i.e. order flow) and bid-ask spreads. Adamati and Pfleiderer (1988) provide a theory to explain why the concentration of trades could occur in particular hours in a domestic trading day. Adamati and Pfleiderer (1988) argue that market activity increases in the opening hours and discretionary liquidity traders tend to cluster their trade when the market is thick; that is, when their trades have little impact on price because of increased market activity. In the absence of adverse selection, when there is time discretion among traders, the relation between trading volume (i.e. order flow) and bid-ask spreads is likely to become negative due to increased market liquidity and decreased inventory risk. Therefore, liquidity traders have strong incentives to trade together and to ensure that trades are concentrated.

Knowing bid-ask spreads are narrower when the market is thick, informed traders will also trade when there are many uninformed liquidity traders trading together, because they also have strong incentives to minimise their trading costs (i.e. little

price impact and narrower bid-ask spreads) by hiding themselves among liquidity traders.

The strategic behaviour of liquidity traders and informed traders then creates an intraday pattern in trading volume (typically U-shaped), as well as in bid-ask spreads. Thus, Adamati and Pfleiderer (1988) predict narrower bid-ask spreads during a period of increased market activity; that is, bid-ask spreads are narrower for larger trades, but they are wider for smaller trades.

Consistent with the theory of Adamati and Pfleiderer (1988), researchers have found U-shaped intraday pattern in average trading volume on the NYSE; namely, heavy trading in the beginning and at the end of the trading day, and relatively light trading in the middle of the day². Inconsistent with the prediction of Adamati and Pfleiderer (1988), however, the NYSE bid-ask spreads are wider, not narrower, during a period of increased market activity, indicating that adverse selection (i.e. risk-averse behaviour) dominates the determination of NYSE bid-ask spreads.

By contrast, in FX markets, where adverse selection does not dominate the determination of bid-ask spreads, and consistent with Adamati and Pfleiderer (1988), researchers find that the relation between trading volume and bid-ask spread is negative, not positive (Bauwens, Omrane & Giot, 2005; Evans & Lyons, 2002; Ito & Hashimoto, 2006; King et al., 2012a; King et al., 2012b; McGroarty, ap Gwilym & Thomas, 2007; McGroarty et al., 2009; Naik et al., 1999; Osler et al., 2004; Osler et al., 2011; Ramadorai, 2008).

Note that the FX market is geographically decentralised, with the most active trading centres located in New York, London and Tokyo (Lyons, 2001). Trading hours from midnight to Hour 4 GMT, from Hour 8 GMT to midday, and from Hour 16 GMT to 20 GMT represent the main trading activity in Tokyo, London and New York, respectively (Ranaldo, 2009).

Studies of intraday analysis of FX markets consistently report three basic patterns in

² Jain and Joh (1986), Wood, McInish and Ord (1985).

trading volume. First, consistent with Adamati and Pflleiderer (1988), the market activity increases in the opening hours and market activity is highest in the overlapping hours of the London and New York markets (Bauwens et al., 2005; Bollerslev & Domowitz, 1993; Ito & Hashimoto, 2006; Ranaldo, 2009). Second, during more active market activity periods, activities are low during lunch hours and, finally, there is a lull in market activity during globally non-active hours, namely Hour 20 to 22 GMT; that is, after the close of the New York trading session. Researchers show that currency bid-ask spreads exhibit the opposite pattern of trading volume. Currency bid-ask spreads are narrower during a period of increased market activity and narrowest in the overlapping hours of the London and New York markets. During active hours, bid-ask spreads are wider during lunch hours and widest during globally non-active hours (Ito & Hashimoto, 2006).

This implies the existence of an intraday pattern in currency bid-ask spreads.

3. Data

The data sets of thirteen currency pairs: The United Arab Emirates Dirham (AED/USD); the Australian dollar (AUD/USD); the Bahraini Dina (BHD/USD); the Chinese Yuan (CNY/USD); the Euro (EUR/USD); the Great Britain pound (GBP/USD); the Hungarian Forint (HUF/USD); the Israeli Shekel (ILS/USD); the Korean won (KWD/USD); the Norwegian Krone (NOK/USD); the Polish Zloty (PLN/USD); the Romanian New Leu (RON/USD); and the South African rand (ZAR/USD): all against US dollars, is drawn from Thomson Reuters, which is one of two main electronic brokered platforms that are dominant in the Commonwealth and Scandinavian currencies (Danielsson et al., 2002; McGroarty et al., 2009). EBS is the other of these two main electronic brokered platform and dominates currencies involving the Euro and US dollars. According to the Bank for International Settlements (2001), between 85% and 95% of interbank trading occurs through these two electronic broker platforms in 2000, with the two platforms forming the interdealer FX market.

The raw dataset is composed of transaction level information; including (1) a date and time stamp to the nearest second (Greenwich Mean Time (GMT)) for every transaction, (2) the best ask and bid prices per second, and (3) the transaction price. The data provide no information about the trade direction. I follow the algorithm presented in Lee and Ready (1991) in assigning the trade direction to each trade. A trade is classified as a “buyer-initiated trade” if the trade price is greater than the midquote. A trade is classified as “seller-initiated” if the trade price is less than the midquote. The midquote is defined as the average of the best bid and best ask prices. Trades executed exactly at the midpoint are classified as neither buyer nor seller initiated and contribute zero to order flow. Order flow is defined as the buyer-initiated trades less the seller-initiated trades, as in Evans and Lyons (2002). The currency bid-ask spread is defined as the ask price less the bid price and is measured relative to the midquote.

Our definition of *one day* corresponds to a trading day, defined as the interval between 00:00 and 23:30. I have partitioned the trading day into forty-seven

successive thirty-minute intervals.

I summarise the statistical properties of the 13 currency pairs in Table 1. At the daily level, the Australian dollar (AUD/USD) is the most heavily traded currency pair and the Great Britain pound (GBP/USD) follows closely behind. Currency bid-ask spreads for the highly liquid Australian dollar (AUD/USD) and Great Britain pound (GBP/USD) are relatively smaller than for all other currencies (with the exception of the Bahraini Dina (BHD/USD)). The currency bid-ask spreads for the least-traded currency pairs; the Chinese Yuan (CNY/USD), and the Romanian New Leu (RON/USD); are relatively higher than for all of the other currencies.

As detailed in the literature review, narrower bid-ask spreads for heavily traded currency pairs suggests that, consistent with Naik et al. (1999); who show that greater market transparency reduces adverse selection; adverse selection does not dominate the currency bid-ask spread. It also suggests that, in the absence of adverse selection, consistent with Adamati and Pfleiderer (1988); who show that bid-ask spread is narrower during a period of increased market liquidity; the relation between bid-ask spreads and order flow is negative.

Table 1 below presents the statistical properties of the 13 currency pairs. In the Currency pairs' column the country name is used for the corresponding exchange rate i (e.g. Australia for Australian dollar) against the US dollar (USD). The daily trading activity indicates the average number of daily trades and the daily bid-ask spread is measured in 10,000 basis points.

Table 1: Statistical properties of the 13 currency pairs

Currency (/US Dollar) pairs	Sample Period		Daily	
			Trading activity	Daily bid-ask Spread (in 10,000 basis point)
UAE	27-Apr-10	30-Apr-13	7	3.38
Australia	18-Apr-97	30-Apr-13	12,591	2.60
Bahrain	27-Apr-10	22-Apr-13	2	1.37
China	26-Sep-10	18-Mar-11	3	146.07
Euro	1-Jan-99	30-Apr-13	1,720	4.38
Great Britain	18-Apr-97	30-Apr-13	8,403	1.81
Hungary	26-Jun-01	30-Apr-13	6	29.08
Israel	4-Apr-99	30-Apr-13	272	23.69
Korea	27-Apr-10	30-Apr-13	3	16.28
Norway	11-Jul-01	19-Dec-12	36	15.84
Poland	10-Nov-99	30-Apr-13	61	29.98
Romania	6-Dec-05	28-Apr-13	5	152.15
South Africa	18-Apr-97	30-Apr-13	1,778	9.17

The summary statistics represent the time-series statistics of the daily average of the trading activity and currency bid-ask spreads for 13 currency pairs: The United Arab Emirates Dirham (AED/USD); the Australian dollar (AUD/USD); the Bahraini Dina (BHD/USD); the Chinese Yuan (CNY/USD); the Euro (EUR/USD); the Great Britain Pound (GBP/USD); the Hungarian Forint (HUF/USD); the Israeli Shekel (ILS/USD); the Korean won (KWD/USD); the Norwegian Krone (NOK/USD); the Polish Zloty (PLN/USD); the Romanian New Leu (RON/USD); and the South African rand (ZAR/USD).

4. Models

In Section 4, I provide forecasting models to test the first hypothesis (H1) and the two complementary hypotheses, (H1.1) and (H1.2). In Section 4.2, I provide a model for the intraday pattern in the currency bid-ask spread.

4.1. Forecasting model

In this section, I provide models to test the first hypothesis and the two complementary hypotheses: (H1) order flow has forecasting power for future exchange rate returns and future currency bid-ask spreads; (H1.1) exchange rate return is positively related to contemporaneous order flows; and (H1.2) currency bid-ask spread is positively related to contemporaneous order flow.

In this paper, I test the forecasting ability of order flow for future order flow and currency bid-ask spread in four steps.

First, I provide a model to test the persistent impact of order flow itself at 30-minute intervals.

Second, I provide models to test two complementary hypotheses; (H1.1), and (H1.2).

Third, based on the first and second steps, I develop a model to test the first hypothesis (H1): (lagged) order flow has forecasting power for future exchange rate returns and future currency bid-ask spreads. The intuition is that if the impact of order flow is persistent at short to medium horizons (i.e. the first step), and if order flow is contemporaneously related to exchange rate return and the bid-ask spread, then the lagged order flow should provide forecasting power for future exchange rate returns and future bid-ask spreads.

Finally, I evaluate the forecasting performance of order flow specification in three ways in terms of; (1) generating returns, (2) forecasting accuracy, and (3)

performance stability under market volatility.

In addition, I also provide a model to test the intraday pattern of currency bid-ask spreads.

4.1.1. Order flow forecasting model

In this section, I provide a model to test the persistent impact of order flow itself at 30-minute intervals; order flow is a dependent variable, and lagged order flow is an explanatory variable. I regress order flow on lagged order flow to examine the forecasting predictability of order flow. I consider the following predictive regression model:

$$NTO_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p NTO_{i,\tau-1} + \varepsilon_{i,\tau} \quad (1)$$

where $NTO_{i,\tau}$ is order flow of currency pair i at time interval τ and $NTO_{i,\tau-1}$ is lagged order flow of currency pair i at time interval $\tau - 1$

As shown in the literature review, in the interdealer FX market, order flow is driven by large banks who are viewed as being more informed (Menkhoff & Schmeling, 2010) and, consistent with Bacchetta and Wincoop (2006), the impact of order flow is persistent at short to medium horizons, while the price continues moving in the direction implied by the information even after the first dealer (who is viewed as being informed) has traded (Osler et al., 2011). This implies that future order flow should be positively related to lagged order flow.

Thus, consistent with Bacchetta and Wincoop (2006), who hold that the impact of order flow is persistent at short to medium horizons, the coefficient β on order flow should be positive. Therefore, the model in Equation (1) predicts that future order flow should be positively related to the lagged order flow.

The estimation results for Model (1) are presented in Table 1 of the empirical results section (Section 5).

4.1.2 Contemporaneous exchange rate return-order flow model

In this section, I test how order flow is contemporaneously related to exchange rate return. Thus, I provide a model to test the first complementary hypothesis (H1.1): Exchange rate return is positively related to contemporaneous order flow.

As determined in the literature review, the relevant theory is information theory, as developed by Glosten and Milgrom (1985). This section concerns the first implication of the information theory; that order flow conveys information about future price fundamentals and dealers adjust prices in response to order flow. This implies that buyer-initiated trades push up price and seller-initiated trades push down price

Each trade is categorised as either buyer, or seller, initiated, as in Lee and Ready (1991), and trades are aggregated in 30-minute intervals. Buyer-initiated trades correspond to positive values of net order flow and seller-initiated trades correspond to negative values (Kyle, 1985). Exchange rate return is a dependent variable and order flow is an explanatory variable. I regress exchange rate return on order flow, using the following regression model:

$$\Delta P_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p NTO_{i,\tau} + \varepsilon_{i,\tau} \quad (2)$$

where $\Delta P_{i,\tau}$ (price return) is $\log P_{i,\tau} - \log P_{i,\tau-1}$ (price change due to order flow), $NTO_{i,\tau}$ ³ is order flow of currency pair i at time interval τ and $P_{i,\tau}$ is the price at which the last trade occurred within the time period.

The coefficient β on order flow should be positive. Thus, the model in Equation (2) predicts that exchange rate return is positively related to contemporaneous order flows.

The estimation results for Model (2) for the 13 currency pairs are presented in Table 2 of the empirical results section (Section 5).

³ NTO is the net turnover of buyer-initiated trades and seller-initiated trades.

4.1.3 Contemporaneous Currency Spread–Order flow model

In this section, I test how order flow is contemporaneously related to bid-ask spread. Thus, I provide a model to test the second complementary hypothesis (H1.2): Currency bid-ask spread is contemporaneously positively related to order flow.

This section concerns the second implication of the information theory in Glosten and Milgrom (1985), that uninformed dealers must widen bid-ask spread to protect themselves from adverse selection when faced with the possibility of trading with informed traders. Order flow is a proxy for private information, as larger trades are more likely to be undertaken by privately informed traders. This implies that bid-ask spreads are wider for larger trades.

In this paper, currency bid-ask spread is defined as the ask price less the bid price and measured relative to the midquote. I use absolute order flow as a proxy for trade volume, because absolute order flow is appropriate for measuring relationships with the bid-ask spread, which involves non-negative variables (McGroarty et al., 2009). Currency bid-ask spread is a dependent variable and absolute order flow is an explanatory variable. Thus, I consider the following linear regression model, using 30-minute intervals:

$$S_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p |NTO| + \varepsilon_{i,\tau} \quad (3)$$

where $S_{i,\tau}$ is the currency bid-ask spread for currency pair i at time interval τ , $|NTO|_{i,\tau}$ is the absolute order flow of currency pair i at time interval τ and $S_{i,\tau}$ is the spread at which the last spread occurred within the time period.

The coefficient β on order flow should be positive. Thus, the model in Equation (2) predicts that the bid-ask spread is positively related to contemporaneous order flows.

The estimation results for Model (3) for the 13 currency pairs are presented in Table 3 of the empirical results section (Section 5).

4.1.4. Spread forecasting model

In this section, I provide a model to test the first implication (H1): (Only for future bid-ask spread) order flow has forecasting power for future currency bid-ask spread.

Bid-ask spread is a dependent variable and lagged order flow is an explanatory variable.

Based on the first (Section 4.1.1) and second steps (Section 4.1.3), I develop a model to test the first hypothesis (H1): (Lagged) order flow has forecasting power for future exchange rate returns and future currency bid-ask spreads.

The intuition is that, if the impact of order flow is persistent at short to medium horizons as suggested in Section 4.1.1 (the first step) and, if order flow is contemporaneously related to bid-ask spread as suggested in 4.1.3 (the second step), then this is consistent with Bacchetta and Wincoop (2006), that the impact of order flow is persistent at the short to medium horizon, and that lagged order flow should provide forecasting power for future exchange rate returns and future bid-ask spreads.

Thus, I consider the following predictive regression model:

$$S_{i,\tau} = \alpha_{it}^p + \beta_{it}^p |NTO|_{i,\tau-1} + \varepsilon_{i,\tau} \quad (4)$$

where $S_{i,\tau}$ is the currency bid-ask spread, $|NTO|_{i,\tau-1}$ is the lagged absolute order flow and $\varepsilon_{i,\tau}$ is an error term.

The persistent impact of order flow at short to medium horizons (Bacchetta & Wincoop, 2006) implies the coefficient β on lagged order flow has to have the same sign as the coefficient in Equation (3).

The estimation results for Model (4) for the 13 currency pairs are presented in Table 4 of the empirical results section (Section 5).

4.1.5. Volatility forecasting model

In this section, I provide a model to test the performance stability of two forecasting models under market volatility, at a daily horizon: (1) The moving average model; and (2) the order flow model.

The root mean squared error (RMSE) is a dependent variable and the volatility of the bid-ask spread (measured in standard deviations) is an explanatory variable. I regress the RMSE on the standard deviation of the bid-ask spread, as follows:

$$RMSE_{i,\tau} = \alpha_{it}^p + \beta_{it}^p \sigma(S)_{i,\tau} + \varepsilon_{i,\tau} \quad (5)$$

where $RMSE_{i,\tau}$ is the root mean squared error for exchange rate i (e.g. Australian Dollar/US Dollar (AUD/USD)) at daily horizon τ . $\sigma(S)_{i,\tau}$ is the standard deviation of the bid-ask spread, which measures the volatility of the spread.

The intuition is that the error in forecasting performance increases during a period of increased market volatility. Thus, the coefficient β on the volatility of bid-ask spread should be positive. The model in Equation (5) predicts that the error in RMSE increases when there is an increase in the volatility.

The estimation results for Model (5) for the 13 currency pairs are presented in Table 7 and Table 8 for (1) the moving average model and (2) the order flow model, respectively, in the empirical results section (Section 5).

4.2. A model for Intraday Spread Patterns

In this section, I test for intraday patterns of currency spreads for the 13 currency pairs over their full sample periods, using 30-minute intervals within each trading day.

I test the intraday pattern of trading volume theory outlined in Adamati and Pfleiderer (1998), which predicts narrower bid-ask spreads during a period of increased market activity because trades have little impact on price due to an increased market activity and large trades enable dealers to reduce inventory risk (Ho & Stoll, 1983). The theory, thus, also predicts a negative relation between bid-ask spreads and order flow; that is, bid-ask spreads are narrower during a period of increased market activity, whereas bid-ask spreads are wider during non-active periods.

I consider the following regression model to test the intraday pattern of spreads, using 30-minute interval dummy variables; the bid-ask spread is a dependent variable, and the 47 half-hour (i.e. 00:00 to 23:30) interval dummy variables are the explanatory variables:

$$S_i = \alpha_0 + \alpha_t d_t + \varepsilon_{i,t} \quad (6)$$

where S_i is the bid-ask spread for currency pair i and $\alpha_t d_t$ is 47 half-hour (i.e. 00:00 to 23:30) interval dummy variables (the subscript t is the corresponding half-hour interval from 00:00 to 23:30). Each interval dummy variable takes the value 1 when the bid-ask spread is recorded in the t half-hour interval, and 0 otherwise

The estimation results for Model (6) for the 13 currency pairs are presented in Figures 1 to 5 of the empirical results section (Section 5).

5 Empirical Results

In Section 5.1, I examine the forecasting ability of the order flow model by evaluating the first hypothesis and the two complementary hypotheses: (H1) Order flow has forecasting power for future exchange rate returns and future currency bid-ask spreads; (H1.1) exchange rate return is positively related to contemporaneous order flows; and (H1.2) currency bid-ask spread is positively related to contemporaneous order flow.

In Section 5.2, I examine the intraday pattern of currency bid-ask spread that suggests periods during which bid-ask spreads are narrower, in which trading costs can be minimised. I also use these results when developing the moving average model.

In Section 5.3, I then evaluate the forecasting performance of the order flow model in three ways; in terms of (1) generating returns, (2) forecasting accuracy, and (3) performance stability under market volatility; relative to the three following naïve forecasting models; (1) the buy-and-hold strategy, (2) the naïve random walk model, and (3) the moving average model.

5.1 Forecasting ability analysis

In this section, I examine the forecasting ability of the order flow model for future order flow and currency bid-ask spread in four steps by evaluating the first hypothesis and the two complementary hypotheses.

First, I examine the persistent impact of order flow itself at 30-minute intervals, using Equation (1).

Second, I examine the two complementary hypotheses (H1.1) and (H1.2): How order flow is contemporaneously related to exchange rate return and bid-ask spread: using Equations (2) and (3).

Finally, I examine the first hypothesis (H1): (Only for future bid-ask spread) order flow has forecasting power for future currency bid-ask spreads at 30-minute intervals: using Equation (4).

5.1.1. Order flow forecasting

In this subsection, I examine the persistent impact of order flow itself at 30-minute intervals, using Equation (1).

Table 1 presents the estimation results for Equation (1) at 30-minute intervals, for the 13 currency pairs over their full sample periods. The results are corrected for heteroskedasticity.

Consistent with the scapegoat theory of Bacchetta and Wincoop (2006) that the impact of order flow is persistent at short to medium horizons, the sign of the coefficients on the lagged order flow (NTO) for all exchange rates is positive, and 10 of the 13 currency pairs are significant at the 1% level (in bold) at 30-minute intervals. The results confirm the finding of Daniélsson et al. (2002), who show that past information on order flow has strong forecasting power for future order flow at short horizons (i.e. ranging from 5-minutes to 30-minutes).

The results here support the finding of Osler et al. (2011) that order flow continues moving in the direction of dealers, who are viewed as more informed, even after their trades. Thus, the results provide further support for the conclusion of Menkhoff and Schmeling (2010) that order flow in the interdealer FX market is driven by large banks, which are viewed as more informed.

Next, I examine two complementary hypotheses (H1.1) and (H1.2); how order flow is contemporaneously related to exchange rate return and bid-ask spread; using Equations (2) and (3).

Table 1
Order flow forecasting Model

$$NTO_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p NTO_{i,\tau-1} + \varepsilon_{i,\tau}$$

The dependent variable $NTO_{i,\tau}$ is the order flow for each exchange rate i (e.g. Australian Dollar/ US Dollar (AUD/USD)), sampled at 30-minute intervals over their full sample periods (τ). In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $NTO_{i,\tau-1}$ is the lagged order flow. Trades are aggregated over 30-minute intervals from 00:00 to 23:30 GMT. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987) and the coefficients in bold are significant at the 1% level (i.e. t-stat=1.96). Column 1 presents the exchange rates against the US Dollar. Positive order flow implies the net purchase of foreign exchange rates.

Currency (/US Dollar) pairs	α (x1,000)	t-stat	β (x1,000)	t-stat
UAE	-241.80	-10.05	66.91	3.53
Australia	628.72	7.53	106.60	5.75
Bahrain	-475.44	-2.76	92.34	0.72
China	-8.08	-0.07	297.45	2.72
Euro	226.91	4.55	110.58	21.65
Great Britain	919.56	13.80	157.50	32.35
Hungary	52.73	0.69	141.16	3.11
Israel	156.30	6.68	165.04	21.42
Korea	-100.85	-1.05	73.91	0.93
Norway	224.92	1.82	156.72	5.19
Poland	-206.19	-7.60	101.20	12.05
Romania	86.99	0.66	103.97	1.00
South Africa	913.72	26.84	152.96	28.85

5.1.2 Contemporaneous exchange rate return-order flow model

In this subsection, I examine how order flow is contemporaneously related to exchange rate returns by evaluating the first complementary hypothesis, using Equation (2).

Table 2 presents the estimation results of Equation (2) at 30-minute intervals for the 13 currency pairs over their full sample periods. The results are corrected for heteroskedasticity. Looking at Table 2, a number of results emerge.

Consistent with Glosten and Milgrom (1985); that exchange rate return is positively related to contemporaneous order flows; the signs of the coefficients on order flow (NTO) for all exchange rates are positive. The striking feature of Table 2 is that the coefficients on order flow (NTO) are statistically significant at the 5% level for virtually all currency pairs (with an exception of the Korean currency) and, of these, ten are statistically significant at the 1% level.

Thus, consistent with Glosten and Milgrom (1985), the results provide strong evidence that order flow conveys information about future exchange rate fundamentals and dealers adjust prices in response to order flow.

The size of the order flow coefficient implies that, for example, for the Great Britain currency (GBP/USD), an additional 10,000 of Great Britain currency (GBP/USD) purchased will increase the currency return by 0.0164 basis points.

The results for Euro and Great Britain currency pairs confirm the finding of Love and Payne (2008), who show that order flow has strong explanatory power for exchange rate fluctuation of the Euro and Great Britain currency pairs at short term horizons. The results further support the finding of Evans and Lyons (2002), who show that price relevant macronews operates through order flow at short to medium horizons.

Table 2
Contemporaneous exchange rate return-order flow model

$$\Delta P_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p NTO_{i,\tau} + \varepsilon_{i,\tau}$$

The dependent variable $\Delta P_{i,\tau}$ is the price return for each exchange rate i (e.g. Australian Dollar/US Dollar (AUD/USD)), sampled at 30-minute intervals (τ) from 00:00 to 23:30 GMT over their full sample periods. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $NTO_{i,\tau}$ is interdealer order flow (i.e. net of buyer-initiated trades and seller-initiated trades) and trades are aggregated over 30-minute intervals from 00:00 to 23:30 GMT. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987), the coefficients in bold are significant at the 5% level of significance (i.e. t-stat=1.96) * indicates a 1% level of significance (i.e. t-stat= 2.58). Column 1 presents exchange rates against the US Dollar. Positive order flow implies the net purchase of foreign exchange rates.

Currency (/US Dollar) pairs	α (x1,000)	t-stat	β (x1,000)	t-stat	R^2
UAE	0.0022	5.50	0.0087	25.95*	21.7%
Australia	-0.0206	-0.90	0.0213	125.92*	0.5%
Bahrain	0.0152	1.61	0.0206	2.54	12.3%
China	-0.0758	-0.28	0.5347	2.62*	6.1%
Euro	-0.0075	-0.25	0.0317	61.71*	0.3%
Great Britain	-0.0182	-10.83	0.0164	134.08*	30.3%
Hungary	-0.2975	-0.05	2.5100	2.25	0.1%
Israel	-0.0204	-0.07	0.0990	4.88*	0.0%
Korea	-0.0418	-0.19	0.2686	1.46	1.4%
Norway	-0.1191	-0.81	0.0641	5.07*	0.3%
Poland	-0.0496	-0.32	0.1813	7.51*	0.1%
Romania	0.2065	0.06	7.3900	2.77*	6.2%
South Africa	-0.0877	-0.77	0.0861	31.72*	0.1%

5.1.3 Contemporaneous Currency bid ask Spread–Order flow model

In this subsection, I examine how order flow is contemporaneously related to bid-ask

spread by evaluating the second complementary hypothesis, using Equation (2).

Table 3 presents the estimation results from Equation (3) at 30-minute intervals for the 13 currency pairs over their full sample periods. The results are corrected for heteroskedasticity.

Table 3
Contemporaneous Spread-Order flow model

$$S_{i,\tau} = \alpha_{i,\tau}^p + \beta_{i,\tau}^p |NTO|_{i,\tau} + \varepsilon_{i,\tau}$$

The dependent variable $S_{i,\tau}$ is the currency spread for each exchange rate i (e.g. Australian Dollar/US Dollar (AUD/USD)) over 30-minute intervals (τ) from 00:00 to 23:30 GMT. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $|NTO|_{i,\tau}$ is the absolute order flow and trades are aggregated over 30-minute intervals from 00:00 to 23:30 GMT. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987) and the coefficients in bold are significant at the 5% level of significance (i.e. t-stat=1.96).

Currency (/US Dollar) pairs	α (x1,000)	t-stat	β (x1,000)	t-stat
UAE	0.0312	38.13	-0.0007	-1.11
Australia	1.1900	64.42	-0.0178	-11.64
Bahrain	0.1441	4.58	-0.0323	-1.94
China	3.6300	1.25	-0.3532	-0.36
Euro	1.8800	24.84	-0.0397	-19.3
Great Britain	0.3130	19.62	-0.0023	-9.12
Hungary	23.9900	3.68	-2.4300	-1.61
Israel	2.0500	20.37	-0.0663	-8.07
Korea	1.4000	8.3	-0.2186	-1.96
Norway	1.1500	9.22	-0.0223	-2.77
Poland	4.6300	18.44	-0.2674	-10.65
Romania	7.1700	1.37	2.5000	0.72
South Africa	1.6600	58.84	-0.0280	-23.72

Inconsistent with the finding of Glosten and Milgrom (1985); that the bid-ask spread is positively related to contemporaneous order flows; the results in Table 3 show that the coefficients on order flow for virtually all currency pairs are negative, which is the opposite of what is predicted by adverse selection. The striking feature of Table 3 is that 8 of the 13 coefficients are statistically significant at the 5% level, providing no support for any implication of adverse selection.

The results presented in Table 3 suggest that adverse selection does not dominate the determination of currency bid-ask spread, supporting the results of previous studies of the behaviour of currency bid-ask spreads, which find that bid-ask spreads vary negatively, not positively, with order flow (King et al., 2012b; McGroarty et al., 2009; Naik et al., 1999; Osler et al., 2004; Osler et al., 2011; Ramadorai, 2008).

Given that the introduction of electronic interdealer markets in the early 1990s has enhanced market transparency, the results here support the conclusion of Naik et al. (1999) that greater market transparency reduces adverse selection and improves market liquidity by encouraging uninformed market participants to participate. Thus, in the absence of adverse selection, the relation between trade volume (i.e. order flow) and bid-ask spread is negative, as suggested by Adamati and Pfleiderer (1988). The empirical evidence here also supports the conclusion of Osler et al. (2004), that in FX markets, dealers have strong incentives to maximise their trading with large traders or with financial customers, who are more likely to be undertake trading when in possession of private information by quoting narrower spreads. Bjønnes et al. (2011) complement the conclusion of Osler et al. (2004) by concluding that in two-tier FX markets, dealers who trade with informed customers in the retail sector can then exploit this private information when trading with other dealers in interdealer FX markets.

In this subsection, I find no evidence to support the second complementary hypothesis (H1.2), that currency bid-ask spread is contemporaneously positively related to order flow. Instead, I find that, in the absence of adverse selection, currency bid-ask spread is contemporaneously negatively related to order flow, supporting the conclusion of Adamati and Pfleiderer (1988), who show that (in the absence of adverse selection), the relation between order flow and bid-ask spread is

negative.

5.1.4 Forecasting future spreads

In this section, I examine the forecasting ability of order flow for the future spreads by evaluating the first hypothesis (H1), using Equation (4): (Only for future bid-ask spread) order flow has forecasting power for future currency bid-ask spread at short to medium horizons. The estimation results of Equation (4) are presented in Table 4.

Consistent with Bacchetta and Wincoop (2006), that the impact of order flow is persistent at short to medium horizons because agents rationally interpret the resulting exchange rate fluctuation as information about future exchange rate fundamentals, the results in Table 4 show that 10 currency pairs have an (expected) negative sign and, of the 10 currency pairs, the coefficient β on 6 currency pairs (Australia, Euro, Great Britain, Israel, Poland and South Africa), is statistically significant at the 1% level.

The results here confirm the finding of Osler et al. (2011), who show that order flow continues moving in the direction of dealers who are viewed as better informed even after their trades. Thus, the results here further support the conclusion of Menkhoff and Schmeling (2010), that the interdealer FX market is driven by large banks that are viewed as more informed.

Finally, the results also support the finding of Huang and Masulis (1999), who show that when a significant number of large banks are in the interdealer FX market, other smaller banks, who are interested in offering liquidity services, later adjust the width of their bid-ask spread so that it matches that of the larger banks.

Table 4
Spreads forecasting model
(Spread - Lagged order flow model)

$$S_{i,\tau} = \alpha_{it}^p + \beta_{it}^p |NTO|_{i,\tau-1} + \varepsilon_{i,\tau}$$

The dependent variable $S_{i,\tau}$ is the currency spread for each exchange rate i (e.g. Australian Dollar/US Dollar (AUD/USD)) at 30-minute intervals (τ) from 00:00 to 23:30 GMT. In the Currency pairs column, the country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $|NTO|_{i,\tau-1}$ is the lagged absolute order flow and trades are aggregated over 30-minute intervals from 00:00 to 23:30 GMT. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987) and the coefficients in bold are significant at the 1% level of significance (i.e. t-stat=1.96).

Currency (/US Dollar)	α (x1,000)	t-stat	β (x1,000)	t-stat
UAE	0.0308	33.36	-0.0003	-0.44
Australia	1.2000	65.99	-0.0192	-14.44
Bahrain	0.0737	2.04	0.0206	0.64
China	3.8700	1.33	-0.5530	-0.57
Euro	1.8500	25.6	-0.0369	-19.18
Great Britain	0.3071	22.77	-0.0019	-14.95
Hungary	24.2400	3.73	-2.6000	-1.70
Israel	2.0500	21.94	-0.0671	-10.52
Korea	1.2800	8.77	-0.1152	-1.55
Norway	1.0100	6.92	0.0115	0.38
Poland	4.6800	17.75	-0.2826	-11.34
Romania	5.2000	0.88	4.1800	0.94
South Africa	1.6600	58.13	-0.0279	-25.02

5.2. Intraday pattern in bid-ask spread

In this section, I examine the intraday pattern of bid-ask spreads using Equation (6) for the 13 currency pairs, at 30-minute intervals, with data covering their full sample periods. Later, I shall use the results from this section when developing the moving average model, which I shall use in the forecasting comparison in Section 5.3.

According to the intraday pattern theory in Adamati and Pflleiderer (1988), bid-ask spreads are narrower during a period of increased market activity; that is, bid-ask spreads are narrower for larger trades, whereas bid-ask spreads are wider for smaller trades. Adamati and Pflleiderer (1988) argue that this creates an intraday pattern in bid-ask spreads. Thus, I evaluate the implications of Adamati and Pflleiderer (1988).

I present the estimation results for Equation (6) at the 30-minute horizon in Figures 1 to 5. The data in this paper consists of four regions, covering Europe, Asia, Oceania and Africa. Figure 1 shows the intraday pattern (hour 00:00-23:30) of bid-ask spreads of two heavily traded non-European currencies; the Australian (Oceania) and South African (Africa) currencies. Figure 2 shows the two most heavily traded European currency pairs; Great Britain and the Euro, along with a Scandinavian currency, Norway. Figure 3 shows the results for the smaller European currency pairs; Hungary, Israel, Poland, and Romania. Figure 4 shows the two Asian currency pairs; China, and Korea. Figure 5 shows the two Middle Eastern currency pairs; the United Arab Emirates, and Bahrain.

Figure 1 shows the intraday patterns of bid-ask spreads for the heavily traded non-European currency pairs; Australia (AUD/USD), and South Africa (ZAR/USD). The intraday patterns of bid-ask spreads in Figure 1 are similar to the typical U-shaped pattern. Although the estimation results for the intraday model outlined in Equation (6) is not reported here, all of the 47 half-hour (30-minutes) dummy variables (i.e. 00:00-23:30) are significant. Figure 1 shows several features of the intraday spreads similar to those reported in previous studies. First, consistent with Adamati and Pflleiderer (1988), spreads are narrower for both currency pairs during domestic

business hours (i.e. 7am to 6pm), indicating that spreads and trading volume move opposingly, and spreads are narrowest in the overlapping business hours of London and New York. Second, during active hours, spreads are wider during lunch time for both the Australian currency (i.e. widens from Hour 12) and the South African currency (i.e. widens around Hour 12). Third, spreads for both currencies are widest after the close of New York sessions. Figure 1 confirms the general U-shaped pattern of spreads documented, in particular, in Ito and Hashimoto (2006).

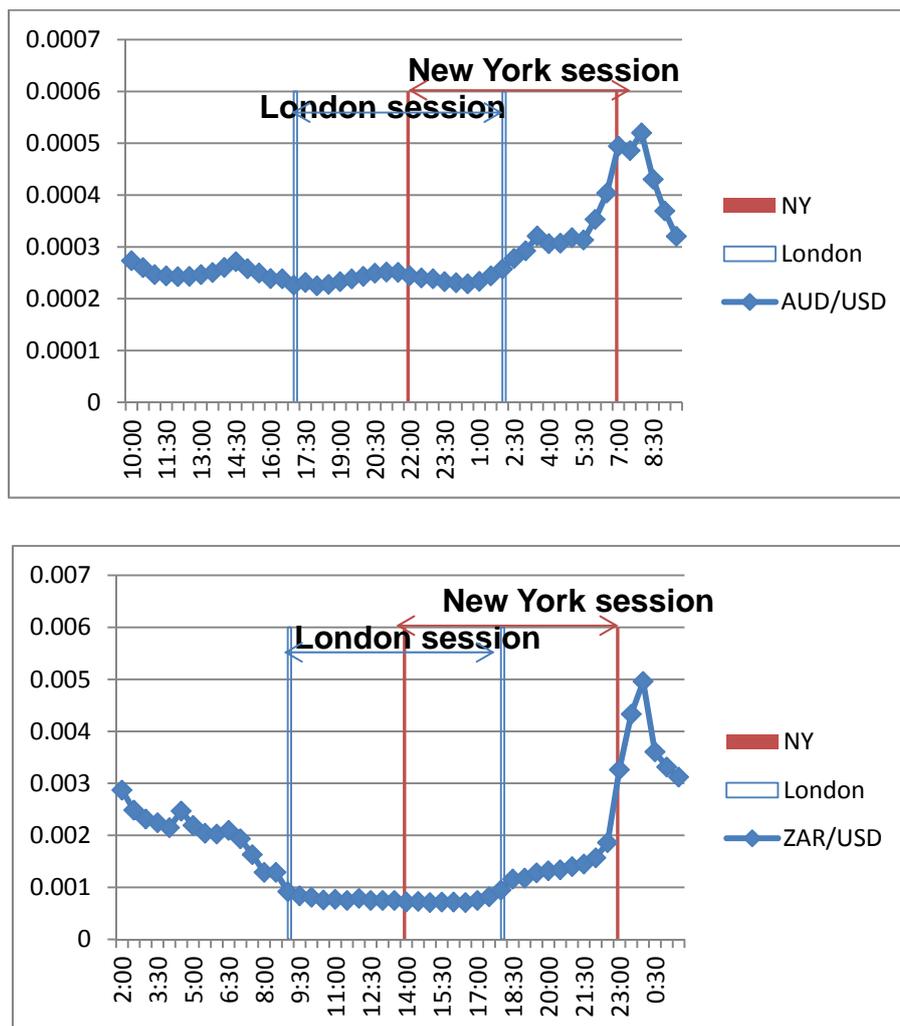


Figure 1: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Australian dollar (AUD/USD) and the South African rand (ZAR/USD).

The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

Figure 2a shows the intraday patterns of bid-ask spreads for the two most heavily traded European currency pairs; the Euro (EUR/USD), and the Great Britain pound (GBP/USD); while Figure 2b shows a Scandinavian currency pair; Norway, which is dominantly traded on the Thomson Reuters platform. Although the estimation results for the intraday model outlined in Equation (3) are not reported here, all 47 half-hour (30-minutes) dummy variables (i.e. 00:00-23:30) for these three currency pairs are significant.

Figure 2a shows several features of intraday bid-ask spreads similar to those reported in previous studies. First, consistent with Adamati and Pfleiderer (1988), during domestic business hours (Hour 7-6), bid-ask spreads are narrower for all three currencies, indicating that spreads and trading volume move oppositely, and bid-ask spreads are narrowest in the overlapping business hours for London and New York. Second, during the active hours, bid-ask spreads are wider during lunch time (i.e. widens around Hour 12) for both the Euro and Great Britain currencies. Third, bid-ask spreads for both currencies are widest after the close of New York sessions. The results for the intraday pattern of spreads of the Euro currency here confirm the finding of Ito and Hashimoto (2006), with the Great Britain currency also confirming the general U-shaped pattern of bid-ask spreads documented in Ito and Hashimoto (2006).

Figure 2b shows several features of the intraday spreads of the Norway currency (NOK/USD) that are similar to those reported in previous studies, but also reveals some different features in the pattern of intraday bid-ask spreads. First, consistent with Adamati and Pfleiderer (1988), during domestic business hours, bid-ask spreads are narrower, indicating that bid-ask spreads and trading volume move oppositely. Bid-ask spreads are, however, narrowest in the hour just before the overlapping business hours in London and New York. Second, during active hours, bid-ask spreads are widest during lunch time, and the bid-ask spread is wider again around 2pm local time. Third, bid-ask spreads are wider after the close of New York sessions. The results for the intraday pattern of spreads for the Norway currency is rather more W-shaped than U-shaped.

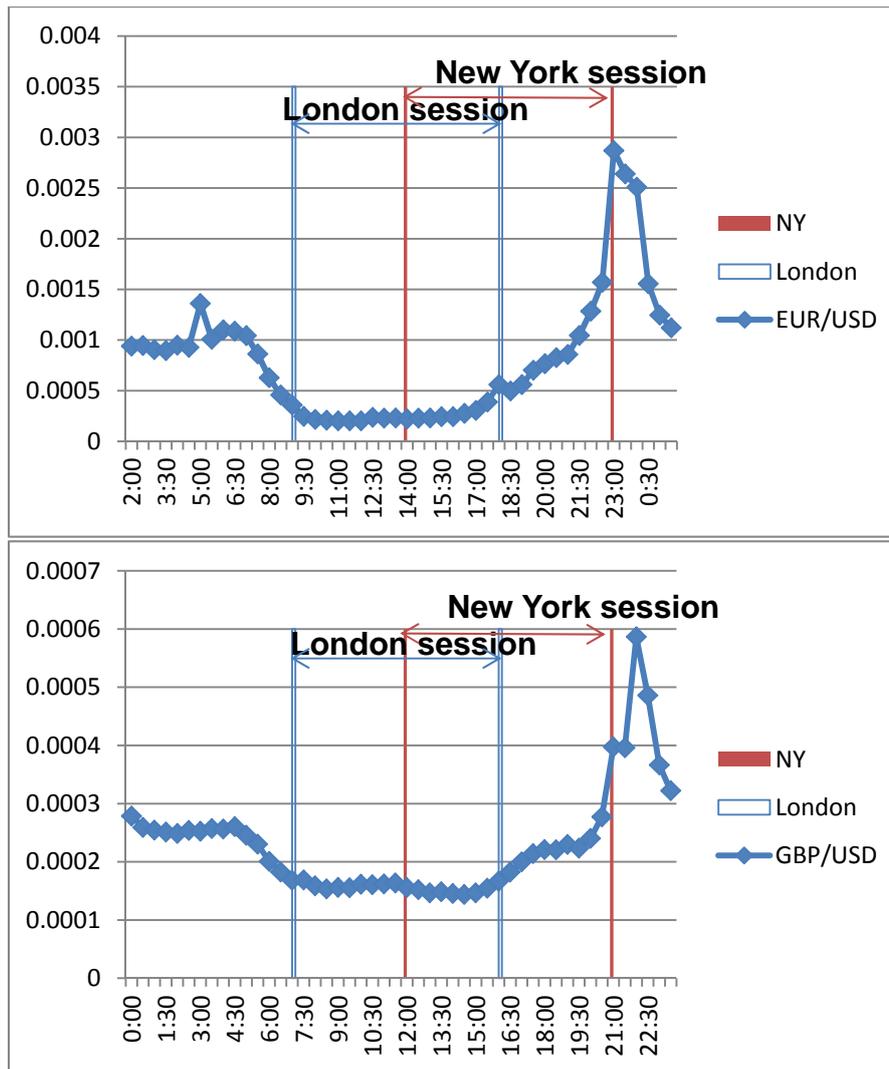


Figure 2a: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Euro (EUR/USD), British Pound (GBP/USD) and Norwegian Krone(NOK/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

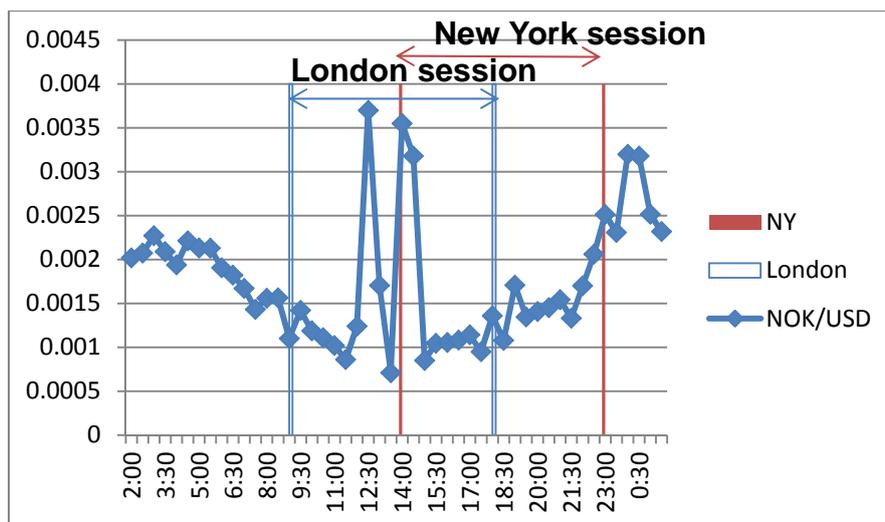


Figure 2b: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Norwegian Krone (NOK/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

Figure 3 shows the intraday patterns of bid-ask spreads for the smaller European currency pairs; Hungary, Israel, Poland (all shown in Figure 3a), and Romania (shown in Figure 3b). Although the estimation results for the intraday model outlined in Equation (3) are not reported here, the 30-minute dummy variables (i.e. 00:00-23:30) for Hungary, Israel and Poland are significant most of time. The 30-minute dummy variables (Hour 0-23) for the Romanian currency (in Figure 3b) are, however, not significant most of time, showing weak evidence that the Romanian currency pair has an intraday pattern in trading volume. Figure 3a shows several features of intraday bid-ask spreads similar to the three basic patterns reported in previous studies. First, consistent with Adamati and Pflleiderer (1988), during domestic business hours (Hour 9-5), bid-ask spreads are narrower for the Hungary, Israel and Poland currency pairs, indicating that spreads and trading volume move oppositely, and bid-ask spreads are narrowest in the overlapping business hours of London and New York. Second, during active hours, bid-ask spreads widen during lunch time (i.e. local time) for the Hungary, Israel and Poland currency pairs. Third, bid-ask spreads for Hungary, Israel and Poland are widest after the close of New York sessions. Figure 3 confirms the general U-shaped pattern of bid-ask spreads documented in Ito and Hashimoto (2006).

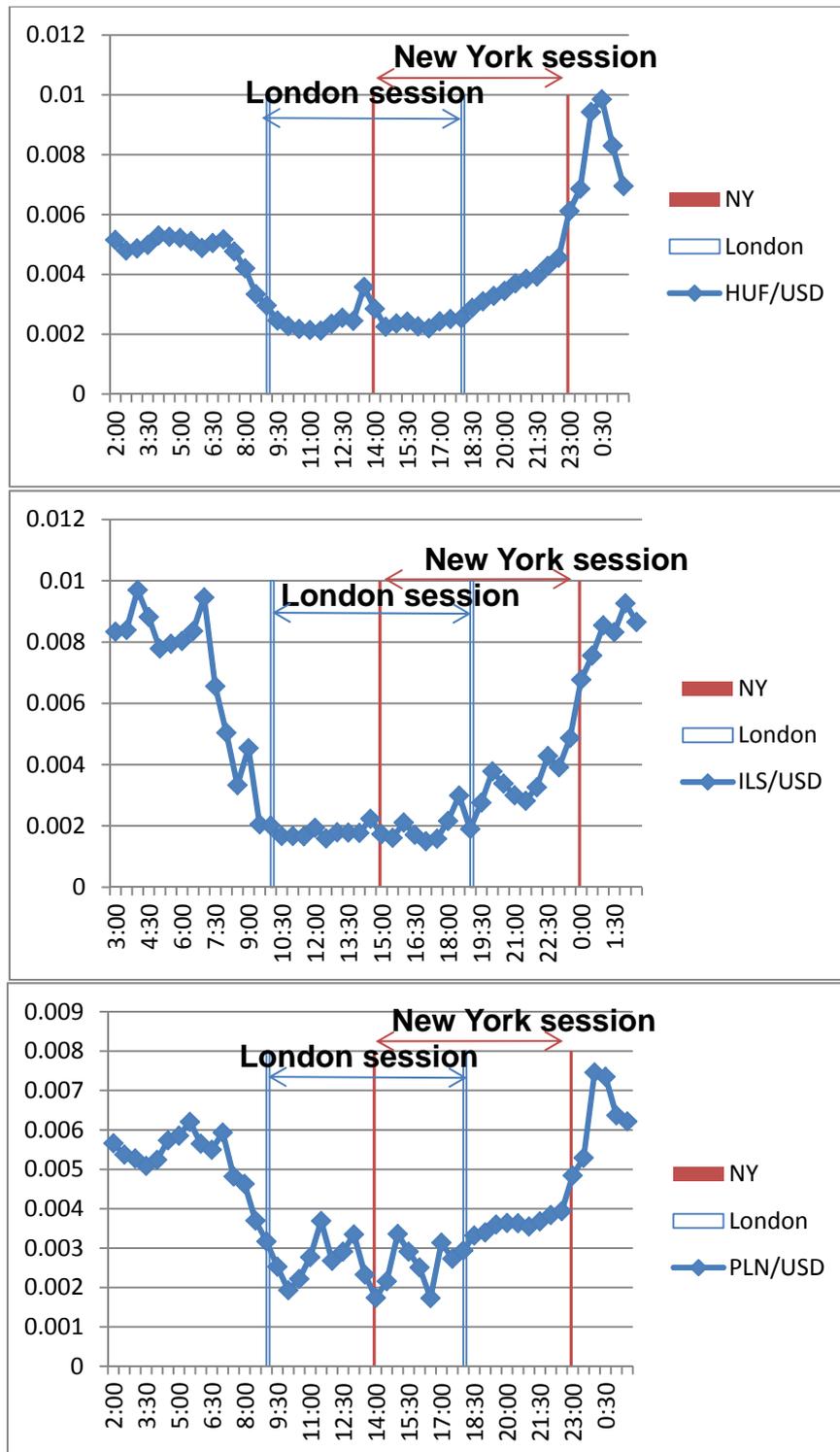


Figure 3a: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Hungarian Forint (HUF/USD), Israeli Shekel (ILS/USD) and Polish Zloty (PLN/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

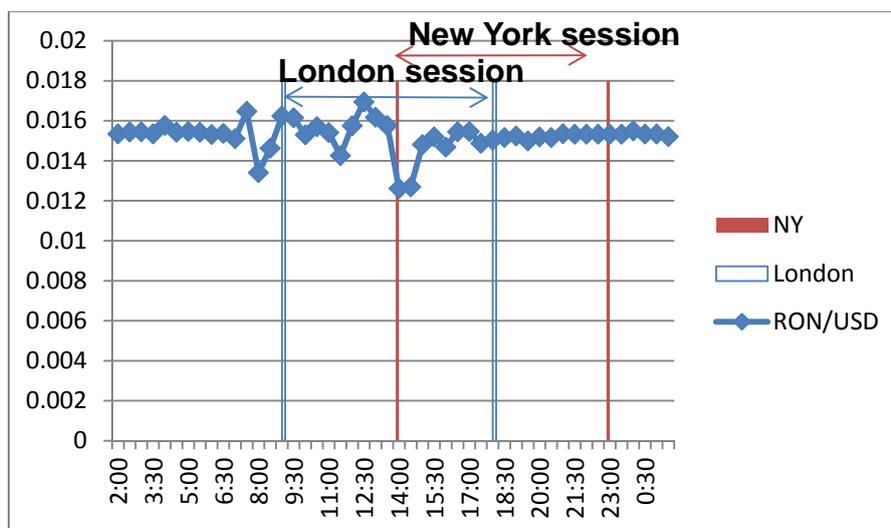


Figure 3b: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Romanian New Leu (RON/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

Figures 4 and 5 show the results for the two Asian currencies (China and Korea) and the two Middle Eastern currencies (the United Arab Emirates and Bahrain). Although the estimation results for the intraday model outlined in Equation (3) are not reported here, the 30-minute dummy variables (Hour 0-23) for China, the United Arab Emirates and Bahrain are insignificant most of time. The 30-minute dummy variables (i.e. 00:00-23:30) for the Korean currency are, however, significant only during domestic business hours and, thus, show several features of intraday spreads similar to the three basic patterns reported in previous studies. First, consistent with Adamati and Pfleiderer (1988), during domestic business hours (i.e. 7am-6pm), spreads are narrower, indicating a negative relation between trading volume and spreads, with spreads found to be narrowest in the overlapping business hours of London and New York. Second, during active hours, spreads are wider during lunch time. Third, spreads are wider after the close of domestic trading sessions (rather than after the close of New York sessions). Thus, only the Korean currency from Figure 4 confirms the general U-shaped pattern of spreads documented in Ito and Hashimoto (2006).

The results here show that nine of the thirteen currency pairs, which are all heavily traded currencies; the Australian dollar (AUD/USD), Euro (EUR/USD), British Pound (GBP/USD), Hungarian Forint (HUF/USD), Israeli Shekel (ILS/USD), Korean won (KWD/USD), Norwegian Krone (NOK/USD), Polish Zloty (PLN/USD), and South African rand (ZAR/USD); confirm the general U-shaped pattern of spreads documented in Ito and Hashimoto (2006). First, the spreads are narrower during domestic business hours and narrowest in the overlapping business hours of London and New York, supporting the conclusion of Adamati and Pfleiderer (1988) that market activity increases in the opening hours and, (in the absence of adverse selection) when there is time discretion among liquidity traders, the relation between trading volume and spreads is negative. Second, during active hours, spreads are wider during lunch time. Third, spreads are widest after the close of New York sessions.

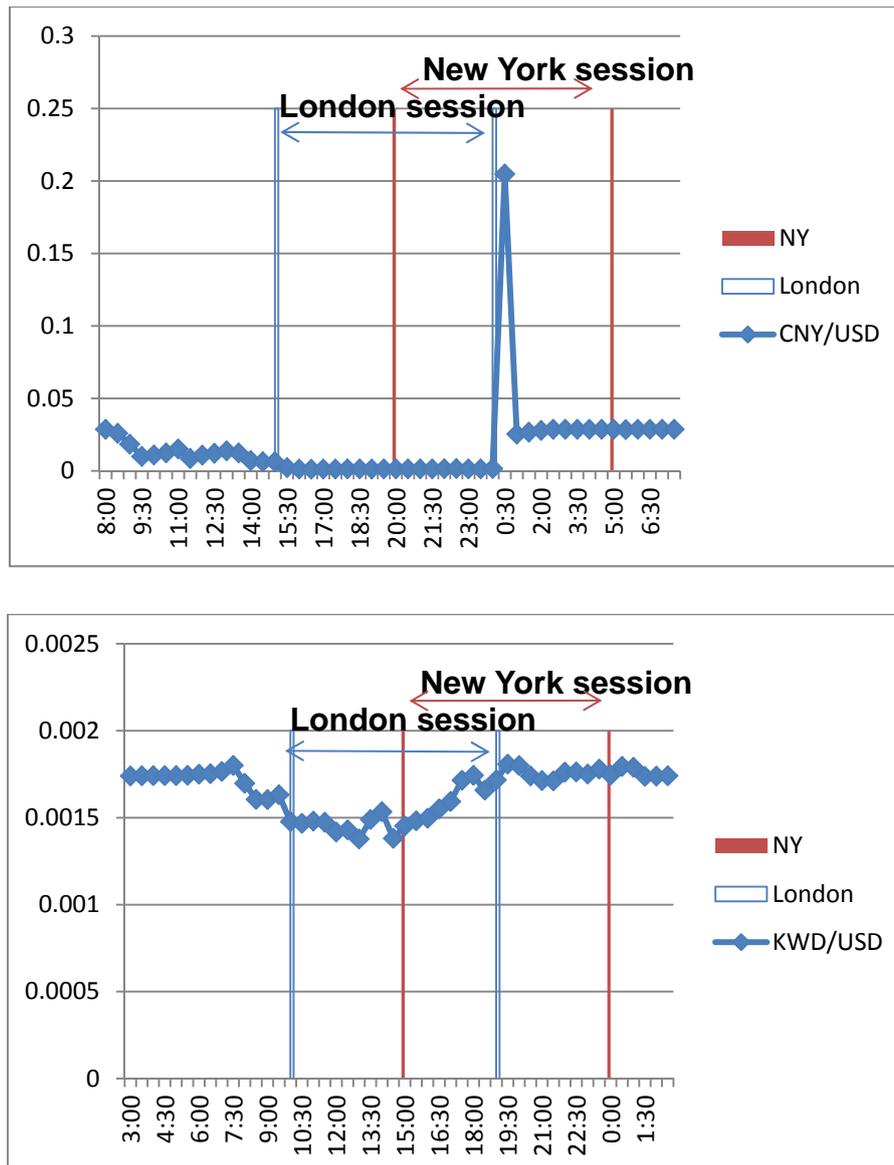


Figure 4: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the Chinese Yuan (CNY/USD) and the Korean won (KWD/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre.

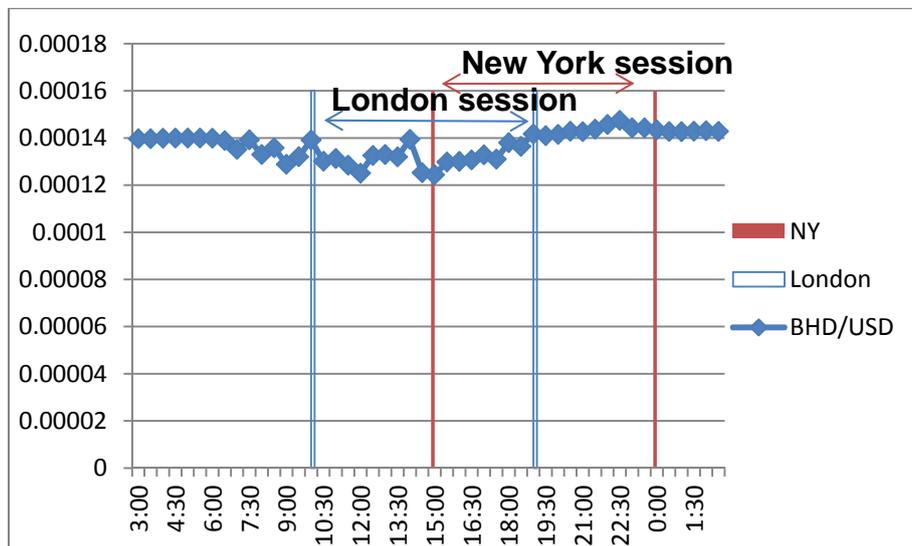
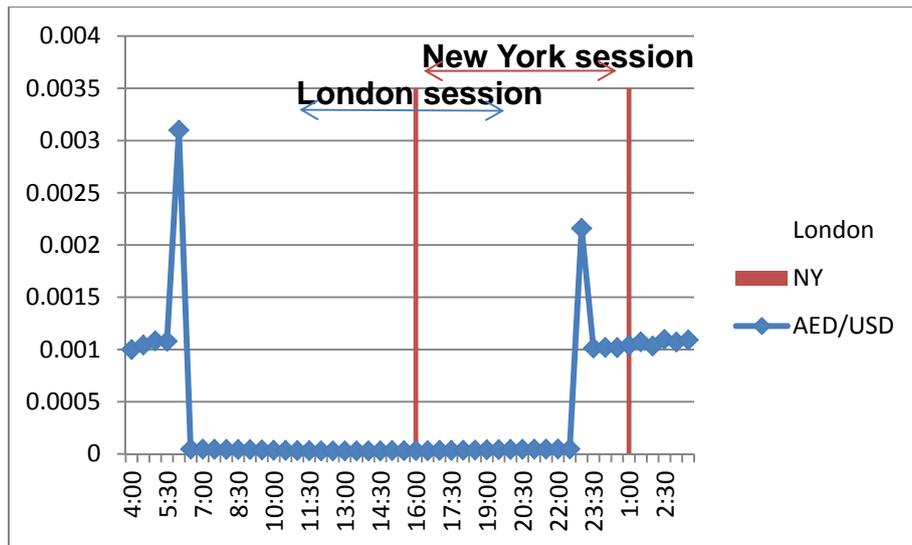


Figure 5: The intraday pattern of spreads (blue diamond shapes) in 30-minute intervals for the United Arab Emirates Dirham (AED/USD) and Bahraini Dina (BHD/USD). The blue bar line indicates the opening and closing hours of the London trading centre, and the red bar line indicates the opening and closing hours of the New York trading centre

5.3. Forecasting performance

In this section, based on the results from Section 5.1, I evaluate the forecasting performance of order flow specification in three ways in terms of; (1) generating returns, (2) forecasting accuracy, and (3) performance stability under market volatility; in relative to the following three naïve forecasting models; (1) a passive trading strategy (buy-and-hold), (2) the widely used benchmark naïve random walk model, and (3) a less sophisticated forecasting model (the moving average model).

5.3.1 Order flow strategy

In this subsection, I evaluate the forecasting performance of order flow at one week horizon in terms of generating returns, relative to the passive trading strategy; the buy-and-hold strategy.

Two trading strategies involve trading the 13 currencies against the US dollar at weekly horizons over their full periods: (1) The order flow strategy (OF), and (2) the buy and hold strategy (BAH), which I shall use in the forecasting comparison.

I develop an order flow strategy based on the results from Table 3 and evaluate the order flow strategy in terms of generating returns, relative to a passive buy-and-hold strategy.

Order flow strategy considers an active trader who rebalances her portfolio weekly each Thursday. She conditions on order flow of the week (i.e. weekly order flow by Thursday) when making a trading decision (buy or sell); sell if the order flow indicates negative, or buy if the order flow indicates positive.

Buy-and-hold strategy is a long-term investment strategy where an investor buys an asset and holds it for a long time. The efficient market hypothesis (EMH) asserts that financial markets are informationally efficient and, thus, every asset is fairly valued at all times (Fama, 1970). Malkiel (2003) argues that active traders do far worse than buy-and-hold investors due to large transaction costs.

Consistent with the first implication that order flow should provide forecasting power for future exchange rate returns and future bid-ask spreads because order flow conveys information about future exchange rate fundamentals, Table 4 of Section 5.1.4 shows that order flow has forecasting power at 30-minute horizons.

This implies that order flow specification should generate higher returns than the buy-and-hold strategy, because the buy-and-hold strategy is based on information about present exchange rate fundamentals, whereas the order flow model is based on information about future exchange rate fundamentals.

I evaluate the forecasting performance of the two models in two steps. First, I calculate the average returns of each model, and second, I construct a new test-statistics (t-statistics) for evaluating whether the difference in returns is statistically significant. The t- statistics are computed as:

(7)

$$t - statistic = \frac{\mu_{OF} - \mu_{BAH}}{\frac{\delta}{\sqrt{n}}}$$

where μ_{OF} , μ_{BAH} are the average returns of the order flow model (OF) and the buy-and-hold model (BAH), respectively. δ is the standard deviation of the difference of both returns. n is the number of observations.

Taking into account the fact that transaction costs can erode returns (Malkiel, 2003), I also consider transaction costs when evaluating returns. Thus, I introduce the break-even transaction cost (BETC). BETC is the return per trade, calculated as follows:

(8)

$$BETC_{i,\tau} = \frac{\text{number of weeks} \times \text{return difference between two models}}{\text{number of trades}}$$

Table 5 presents the weekly performance of the two models.

Table 5
The performance of Order flow and Buy-and-Hold trading strategies

The table shows the out-of-sample performance of the order flow strategy investing in the 13 currency pairs with weekly rebalancing over the full sample periods. The benchmark strategy is the Buy and Hold (BAH) strategy. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The average returns are measured in 10,000 basis points. BETC represents the break-even transaction cost and is measured in 10,000 basis points. The t-statistics determine whether the difference in performance (i.e. average returns) is significantly different at the 5% level (i.e. t-stat=1.96).

Currency (/US Dollar) pairs	Average Returns (in 10,000 basis points)		Difference in the performance of two models	
	Order flow Strategy	Buy & Hold Strategy	t-statistics	BETC (in 10,000 basis points)
UAE	1.29	0.15	0.55	0.0009
Australia	4353.84	340.63	5.06	1.6775
Bahrain	18.57	-2.95	1.74	0.0196
China	900.96	610.78	0.55	0.2408
Euro	2133.76	166.62	5.03	1.6469
Great Britain	1419.24	-52.59	5.24	1.2319
Hungary	4281.55	-1576.48	2.33	4.8911
Israel	883.69	-212.49	4.23	0.9164
Korea	-1094.69	-415.28	-1.4	-0.5995
Norway	1488.75	-1576.53	1.92	2.5706
Poland	1673.09	-459.86	3.39	1.7852
Romania	3054.21	5571.44	-0.16	-2.1044
South Africa	3578.95	847.90	6.42	2.2832

Consistent with the implication from this section that the order flow model should

outperform the buy-and-hold strategy, Table 5 shows that order flow strategies outperform buy-and-hold strategies on virtually all currency pairs at one week horizons; 11 of the 13 currency pairs (indicated in bold). Of these 11 currency pairs, the t-statistics indicate that, for 7 currency pairs; Australia, Euro, Great Britain, Hungary, Israel, Poland and South Africa (indicated in bold); the order flow strategy generates significantly higher returns than the buy-and-hold strategy.

The results here further support the conclusion of Menkhoff and Schmeling (2010), that order flow in the interdealer FX market is driven by large banks, which are viewed as informed dealers. Thus, the results confirm the finding of Bjønneset al. (2011), who report that those large banks that are viewed as most informed have the most positive post-trade returns to their orders.

Consistent with Bacchetta and Wincoop (2006) the impact of order flow is persistent at short to medium horizons, with the results in Table 5 also showing that the impact of order flow is persistent at the one week horizon. This supports the finding of Berger et al. (2008), who show that the impact of order flow remains statistically and economically significant at longer horizons (i.e. at the 3 month horizon).

Taking into account that transaction costs erode returns, Table 5 also provides the break-even transaction costs (BETC) in 10,000 basis points. The break-even transaction cost (BETC) for Australia (AUD/USD), for example, indicates that if the transaction cost is below 1.6775 basis points per trade, the order flow model outperforms the buy-and-hold model.

5.3.2 Forecasting performance of order flow model in RMSE

In this section, I evaluate the forecasting accuracy of order flow relative to the naïve random walk in terms of forecasting accuracy by using root mean square errors (RMSEs), as in previous studies (Evans & Lyons, 2005; Meese & Rogoff, 1983).

The random walk model is the benchmark by which I compare the forecasting performance of the order flow model. The seminal contribution of Meese and Rogoff

(1983); the random walk model; predicts that all forecasts are equal to the last observation. It has become the benchmark for assessing exchange rate predictability, and has the following regression form:

$$S_{i,\tau} = \alpha_{it}^p + S_{i,\tau-1} + \varepsilon_{i,\tau} \quad (9)$$

where $S_{i,\tau-1}$ is the estimated drift based on public information up to time $\tau-1$ only.

Meese and Rogoff (1983) use the root mean squared error (RMSE) to measure the accuracy of forecasting models. The root mean squared error (RMSE) is a good measure of the accuracy of forecasting models, with a smaller value indicating a better fit.

Consistent with the first implication that order flow should provide forecasting power for future exchange rate returns and future bid-ask spreads because order flow conveys information about future exchange rate fundamentals, Table 4 of Section 5.1.4 shows that order flow has forecasting power at the 30-minute horizon.

This implies that order flow specification should provide higher forecasting accuracy and, thus, less forecasting error, since the benchmark naïve random walk model is based on past information about exchange rate fundamentals, whereas the order flow model is based on information about future exchange rate fundamentals.

I evaluate the forecasting accuracy of two models in two steps. First, following Meese and Rogoff (1983), I use the root mean squared error (RMSE) to measure the accuracy of the order flow model and compare it to that of the benchmark random walk (RW) by computing the difference of RMSE. RMSE is computed as follows:

$$RMSE = \sqrt{\frac{(F-A)^2}{n}} \quad (10)$$

where F is the forecast value, A is the actual value, and n is the total number of

forecasts.

I then construct a new test-statistic (t-statistic) to evaluate the significance of the difference in RMSE between the two models. The test-statistics are computed as:

$$t - statistic = \frac{RMSE_{RW} - RMSE_{OF}}{\frac{\delta}{\sqrt{n}}} \quad (11)$$

where $RMSE_{OF}$ and $RMSE_{RW}$ are the RMSEs of the order flow model (OF) and the random walk model (RW), respectively. δ is the standard deviation of the difference of both RMSEs. n is the total number of observations.

I only use the six currency pairs from Table 4 in Section 5.1.4 that show statistically significant coefficients; Australia, Euro, Great Britain, Israel, Poland, and South Africa.

Table 6 presents the results of RMSE Equation (10) and the t-statistic results.

I first provide visual illustrations of the performance of the two models in RMSE in Figures 6 to 8.

First, Figure 6 shows the RMSE of the two models for the non-European currency pairs; Australia, and South Africa; over their full sample periods. Consistent with the implication of this section, that order flow model should provide higher forecasting accuracy and, thus, less forecasting error relative to the naïve random walk, Figure 6 clearly shows that the error generated by the order flow models is lower than that of the benchmark random walk models. The RMSE results in Table 6 for these two currency pairs confirm the impression from Figure 6.

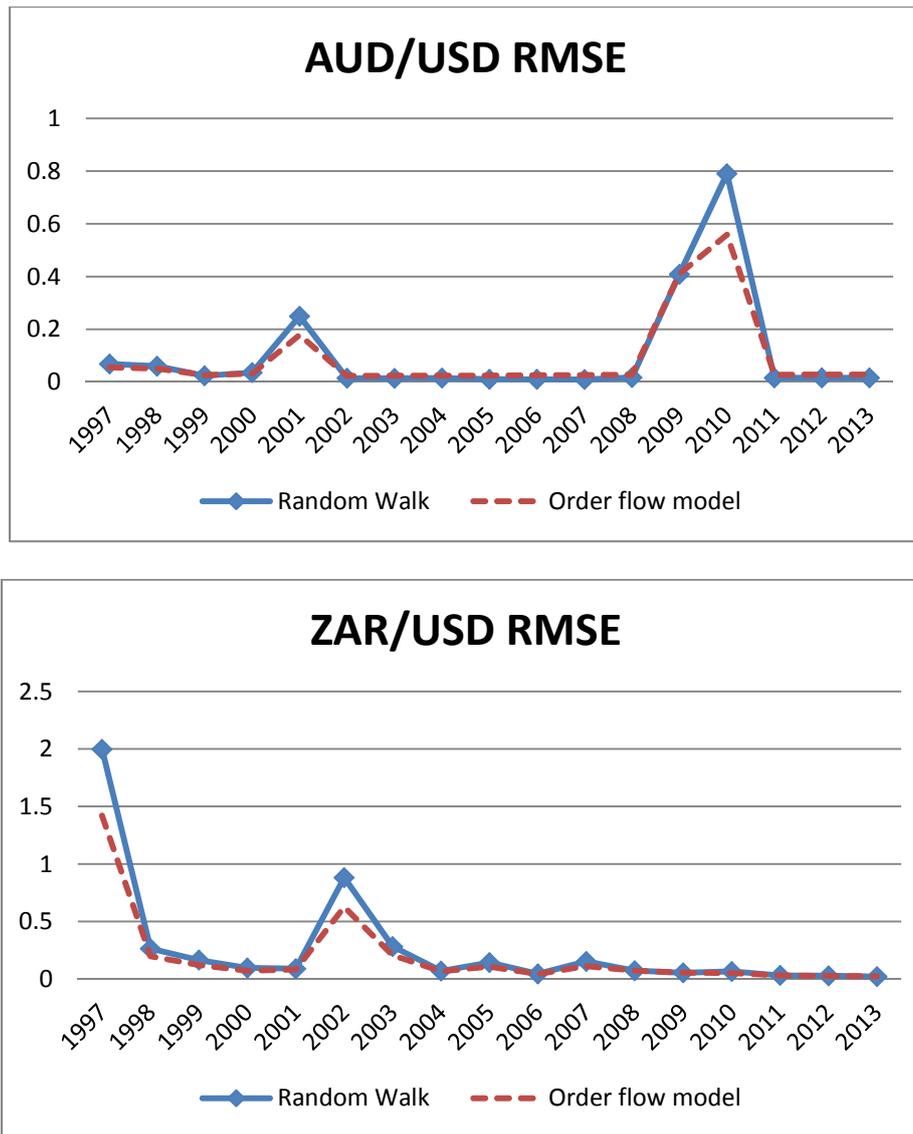


Figure 6: RMSE of the order flow model (blue diamond shaped line) relative to the benchmark random walk (red dotted line) for the heavily traded non-European currency pairs

Next, Figure 7 shows the RMSE of the two models for the two most heavily traded European currency pairs; Great Britain, and Euro; over their full sample periods. Consistent with the implication of this section, that the order flow model should provide higher forecasting accuracy and, thus, less forecasting error relative to the naïve random walk, Figure 7 clearly shows that the error generated by the order flow model is lower than that of the benchmark random walk model. The RMSE results in Table 6 for these two European currency pairs confirm the impression from Figure 7.

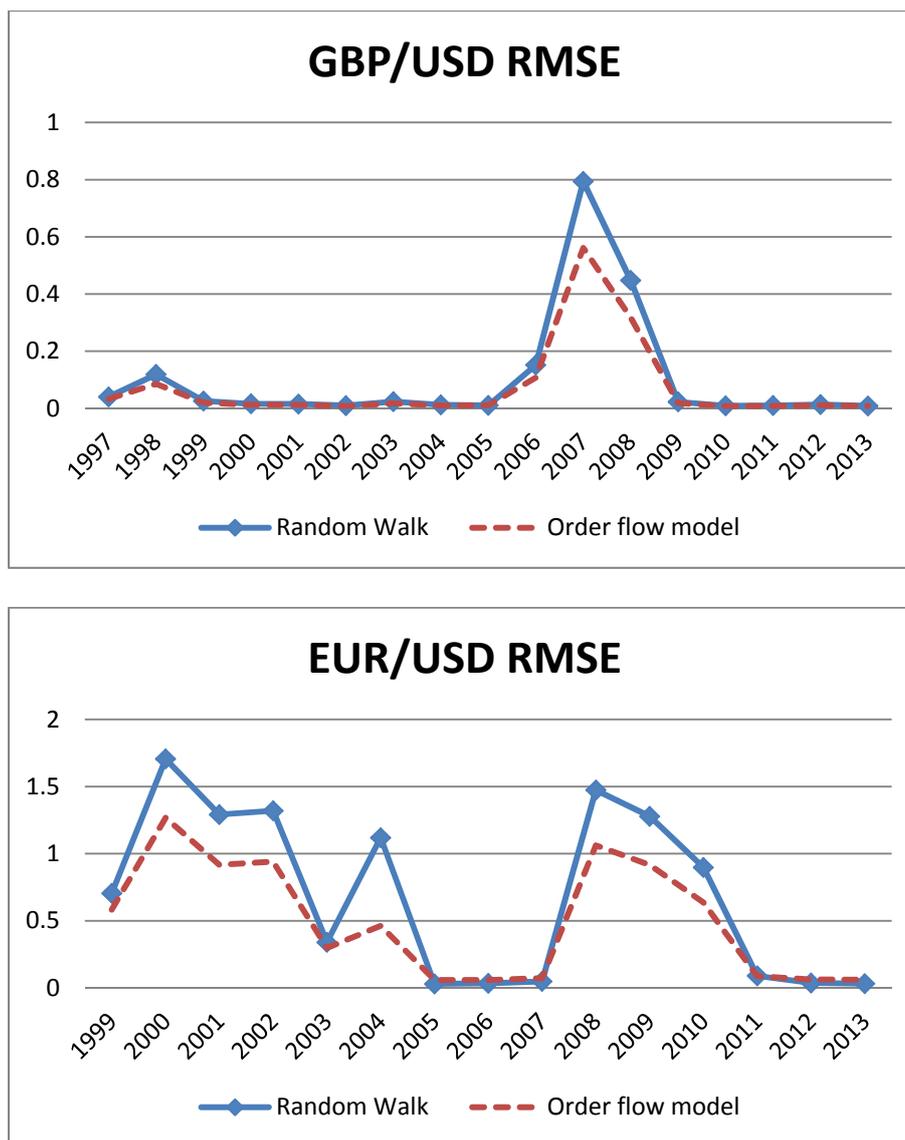


Figure 7: RMSE of the order flow model (blue diamond shaped line) relative to the benchmark random walk (red dotted line) for the two most heavily traded European currency pairs

Figure 8 shows the RMSE of the two models for the other smaller European currency pairs; Israel, and Poland; over their full sample periods. Consistent with the implication of this section, that order flow model should provide higher forecasting accuracy and, thus, less forecasting error relative to the naïve random walk, Figure 8 clearly shows that the error generated by the order flow models is lower than that of the benchmark random walk models. The RMSE results in Table 6 for the Israeli (ILS/USD) and Polish (PLN/USD) currency pairs confirm the impression from Figure 8.

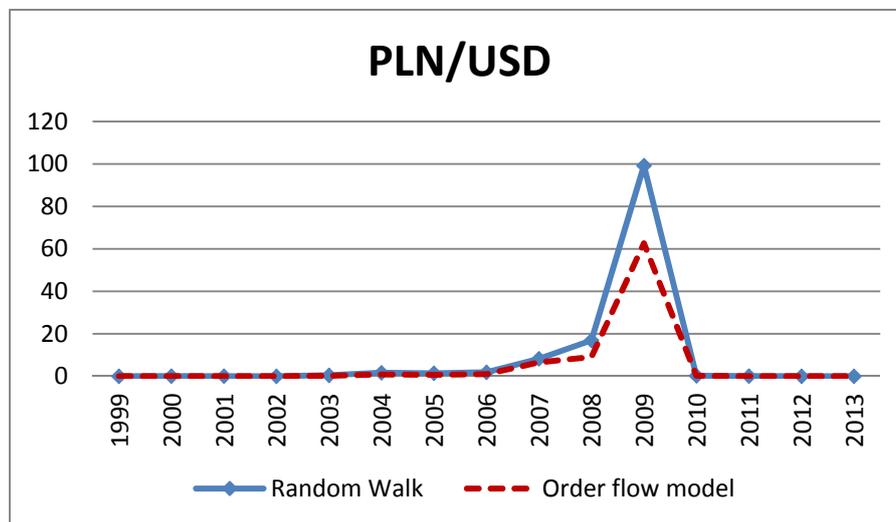
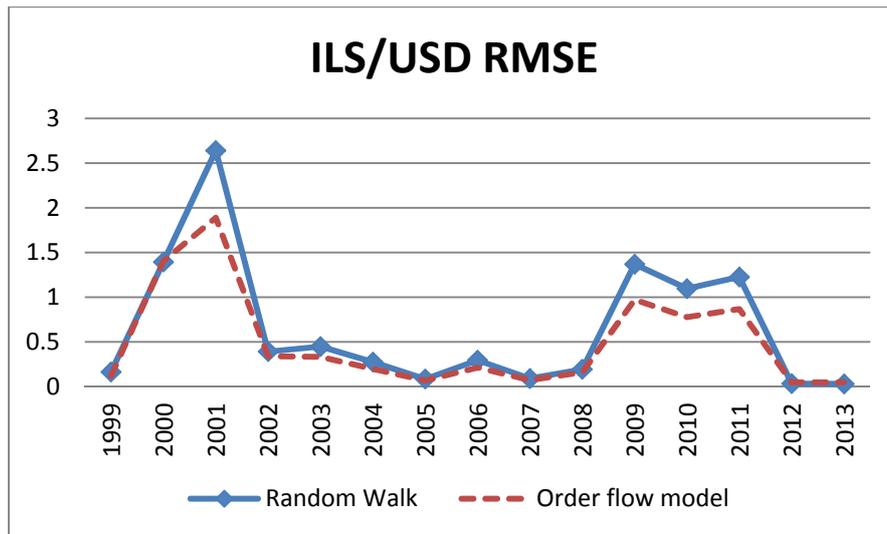


Figure 8: RMSE of the order flow model (blue diamond shaped line) relative to the benchmark random walk (red dotted line) for the two other European currency pairs

Consistent with the implication of this section, that the order flow model should provide higher forecasting accuracy and, thus, less forecasting error relative to the naïve random walk, Table 6 shows that the root mean square errors (RMSEs) generated by the order flow models are all lower than those from the benchmark random walk model at 30-minute intervals.

Thus, the results here further support the conclusion of Menkhoff and Schmeling (2010) that order flow in the interdealer FX market is driven by large banks, which are viewed as informed dealers.

The t-statistic results from Table 6 indicate that the difference in RMSE is statistically significant for the Euro, Israel and Poland currency pairs, whereas for the Australia, Great Britain and South Africa currency pairs, order flow model is a marginally better fit.

Table 6

Summary of RMSE results for Order flow Model and Random Walk Model

The table shows the root mean square errors (RMSEs) statistics for the (spread-lagged) order flow model and the benchmark random walk (RW) for the 13 currency pairs at 30-minute frequency over their full sample periods. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The difference represents the difference in RMSE between the benchmark random walk (RW) model and the (spread-lagged) order flow model. The t-statistic determines whether the difference is significantly different at the 5% level (i.e. t-stat=1.96).

Currency (/US Dollar) Pairs	RMSE		Difference in the performance between two models	
	Random model	Order flow model	Difference	t-stat
Australia	0.0081	0.0058	0.0023	1.42
Euro	0.0291	0.0205	0.0086	4.01
Great Britain	0.0075	0.0053	0.0022	1.35
Israel	0.0255	0.0184	0.0072	2.41
Poland	0.0457	0.0355	0.0102	2.79
South Africa	0.0106	0.0076	0.0030	1.53

The results in Table 6 also confirm the results of Evans and Lyons (2005), who show that the order flow model outperforms the benchmark random walk model in forecasting accuracy.

5.3.3 The performance stability under market volatility

In this subsection, I evaluate the performance stability of order flow model under market volatility, relative to the moving average model.

Since I find an intraday pattern in currency spreads in Section 5.2, I introduce a naïve forecasting model; the moving average model. I only use nine currency pairs that have intraday day patterns from Section 5.2; Australia, Euro, Great Britain, Hungary, Israel, Korea, Norway, Poland, and South Africa.

The moving average model is based on the average of spreads over the past 260 days of each 30-minute interval (from Hour 00:00 GMT to 23:30). Thus, I consider the following moving average model:

$$S_{i,\tau} = \alpha_{it}^p + \beta_{it}^p \bar{S}_{i,\tau} + \varepsilon_{i,\tau} \quad (12)$$

where $\bar{S}_{i,\tau}$ is the average of the spreads over the past 260 trading days of each 30-minute interval (e.g. the average of the spreads over the past 260 days of 00:30 GMT intervals).

I use Equation (6) outlined in Section 4.1.5 to examine the performance stability of forecasting models under market volatility. I then compare the results of the moving average model to those of the order flow model.

Consistent with the first implication that order flow should provide forecasting power for future exchange rate returns and future bid-ask spreads because order flow conveys information about future exchange rate fundamentals, Table 4 of Section 5.1.4 shows that order flow has forecasting power at 30-minute horizons.

This implies that order flow specification should provide more stable, and less volatile, forecasting performance under market volatility relative to the moving average model, as the moving average model is based on the average value of the past information about exchange rate fundamentals, whereas the order flow model is

based on information about future exchange rate fundamentals.

I first examine the performance stability of the moving average model under market volatility, using the nine currency pairs. Table 7 presents the estimation results for the moving average model.

Table 7 shows that all of the coefficients have the predicted (positive) sign. The striking feature of Table 7 is that the coefficients on the volatility of spread for all currency pairs are highly significant at the 1% level, with the t-statistics all above 2.58. This indicates that the performance of the moving average model is highly sensitive to market volatility, suggesting that the error in forecasting increases significantly when the market becomes highly volatile.

Next, I examine the performance stability of the order flow model under market volatility, using the same six currency pairs used in the previous section (Section 5.3.2); Australia, Euro, Great Britain, Israel, Poland, and South Africa. The results are reported in Table 8.

The coefficients on the volatility of the spreads for all six currency pairs have the predicted positive sign, indicating that the performance of the order flow model is also affected by market volatility. Table 8 shows, however, that the coefficients on three of the six currency pairs; Australia, Great Britain, and South Africa; are not statistically significant and are, thus, consistent with the implication of this section that order flow should provide more stable and less volatile performance under market volatility. The results in Table 8 indicate that the performance of the order flow model is more stable and less volatile, relative to the moving average model.

Table 7**Daily RMSE - Volatility of spread model**

$$RMSE_{i,\tau} = \alpha_{it}^p + \beta_{it}^p \sigma(S)_{i,\tau} + \varepsilon_{i,\tau}$$

The dependent variable RMSE is the root mean square errors of the order flow model, as outlined in Equation (5), for each exchange rate i (e.g. Australian Dollar/ US Dollar (AUD/USD)) at daily time intervals. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $\sigma(S)_{i,\tau}$ is the standard deviation of the spread and measures the volatility of the spread. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987) and the coefficients in bold are significant at the 1% level of significance (i.e. t-stat= 2.58). Column 1 presents the exchange rates against the US Dollar. Positive order flow implies the net purchase of foreign exchange rates.

Currency (/US Dollar) pairs	α (x1,000)	t-stat	β (x1,000)	t-stat
Australia	0	0.14	0.2708	5.69
Euro	-0.01	-2.25	10.42	7.05
Great Britain	0.0022	11.09	6.1092	33.06
Hungary	0.0518	13.22	1.2152	9.28
Israel	0.0034	7.61	1.2523	19.59
Korea	0.0006	11.3	1.0748	17.67
Norway	0.0099	7.16	1.3287	3.73
Poland	0.0106	9.91	1.2171	22.99
South Africa	0.0009	4.33	1.1262	20.3

Table8**Daily RMSE - Volatility of spread model**

$$RMSE_{i,\tau} = \alpha_{i,\tau}^p + \beta_{it}^p \sigma(S)_{i,\tau} + \varepsilon_{i,\tau}$$

The dependent variable RMSE is the root mean square errors of the order flow model, as outlined in Equation (5), for each exchange rate i (e.g. Australian Dollar/ US Dollar (AUD/USD)) at daily time intervals. In the Currency pairs column, country name is used for the corresponding exchange rate i (e.g. Australia for Australian Dollar) against the US Dollar (USD). The explanatory variable $\sigma(S)_{i,\tau}$ is the standard deviation of the spread and measures the volatility of the spread. The coefficients of the explanatory variables are scaled up by 1,000. The t-statistics (t-stat) are adjusted for heteroskedasticity (Newey & West, 1987) and the coefficients in bold are significant at the 5% level (i.e. t-stat=1.96), while the coefficients in bold with an * sign are significant at the 1% level (i.e. t-stat=2.58). Column 1 presents the exchange rates against the US Dollar. Positive order flow implies the net purchase of foreign exchange rates.

Currency (/US Dollar) Pairs	α (x1,000)	t-stat	β (x1,000)	t-stat
Australia	0.0009	10.62	0.1310	1.00
Euro	0.0034	11.38	0.1748	2.45
Great Britain	0.0004	7.62	0.0212	1.09
Israel	0.0020	6.13	0.1179	2.26
Poland	-0.0009	-0.45	0.5840	4.05*
South Africa	0.0012	3.34	0.1368	1.27

6. Conclusion

I study the forecasting power of order flow for 13 currency pairs at sampling frequencies ranging from 30 minutes to 1 week, using data for the United Arab Emirates Dirham (AED/USD), the Australian dollar (AUD/USD), the Bahraini Dina (BHD/USD), the Chinese Yuan (CNY/USD), the Euro (EUR/USD), the Great Britain Pound (GBP/USD), the Hungarian Forint (HUF/USD), the Israeli Shekel (ILS/USD), the Korean won (KWD/USD), the Norwegian Krone (NOK/USD), the Polish Zloty (PLN/USD), the Romanian New Leu (RON/USD), and the South African rand (ZAR/USD), all against US dollars.

I show that the order flow forecasting model outperforms three native forecasting models; (1) a passive trading strategy (buy-and-hold), (2) the widely used benchmark naïve random walk model, and (3) a less sophisticated forecasting model (the moving average model), which I use in forecasting comparisons in terms of generating returns, forecasting accuracy and performance stability under market volatility, at all frequencies.

My key results are:

1. Ascertaining the impact of order flow on order flow itself at short to medium horizons;
2. That the impact of exchange rates and bid-ask spreads is persistent at short to medium horizons;
3. That there is an intraday pattern in bid-ask spreads for Australia , Euro, Great Britain, Hungary, Israel, Korea, Norway, Poland, and South Africa currency pairs;
4. That the order flow forecasting model significantly outperforms the buy-and-hold strategy in generating returns;
5. That the order flow forecasting model significantly outperforms the naïve random walk in forecasting accuracy (i.e. RMSE); and
6. That, although there is an intraday pattern in the bid-ask spreads on nine currency pairs, the order flow forecasting model provides more stable and

less volatile performance under market volatility, relative to the moving average model.

Thus, these results emphasise that order flow conveys information about future exchange rate movement, and that the impact of order flow is persistent at short to medium horizons. Thus, a sophisticated forecasting model based on order flow improves returns, forecasting accuracy, and provides stable and less volatile performance under market volatility, relative to naïve forecasting models that are only based on either past or present information about exchange rate fundamentals.

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