Intraday Patterns in FX returns and Order Flow.

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ABSTRACT

We present evidence of time-of-day effects in foreign exchange returns through a significant tendency for currencies to depreciate during local trading hours (e.g. EUR/USD tends to depreciate in the European morning and then appreciate in US trading hours). We confirm this across a range of currencies and find that, in the case of EUR/USD it can form a simple, profitable trading strategy. We also find that this pattern is reflected in order flow and suggest that both patterns relate to the tendency of market participants to be net purchasers of foreign exchange in their own trading hours. Data from alternative sources appear to corroborate that interpretation.

Keywords: Foreign Exchange, Microstructure

JEL-keys: G15

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1. Introduction

This paper investigates predictable time-of-day patterns in FX returns and how they relate to order flow.

Despite an extensive literature on time-of-day effects in other aspects of the FX market such as volatility (e.g. Andersen and Bollerslev (1998)) and turnover (e.g. Hartmann (1999)), there are, as far as we know, only two papers on time-of-day effects in returns (Cornett et al (1995) and Ranaldo (2006)). This gap is all the more surprising given that both these papers find very similar time-of-day patterns in FX returns whereby local currencies tend to depreciate during their own trading hours and appreciate outside them. Both papers also find that this effect is both statistically significant and economically important.

As well as being important in its own right in explaining high frequency exchange rate dynamics, this effect has important implications for our overall understanding of FX markets. In particular, if this time-of-day effect is caused by predictable and uninformative patterns in order flow (which is what our analysis suggests) then our results give support for the traditional portfolio balance effect in FX markets where uninformative (and in this case predictable) changes in demand have a significant impact on returns. Thus the results presented here make an important contribution to the growing evidence that portfolio balance effects are present in FX markets and suggest that liquidity effects are an important (though not necessarily the only) route through which trades relate to FX returns. This evidence comes from a range of sources such as transaction data (Breedon and Vitale (2005)), Institutional flows (Froot and Ramadorai (2005)), events such as equity index rebalancing (Hau, Massa and Peress (2006)) and more recent intervention studies (e.g. Fatum and Hutchinson (2003)) and is beginning to overturn the traditional view that these effects were not present (see for example Rogoff (1983)). In fact, it could be argued that this intraday pattern is amongst the strongest evidence yet for liquidity effects since it can be observed in a large sample (rather than one-off events like index changes) and seems a clear case of a pattern of trades that cannot be related to private information so their impact on prices is uncontaminated by information effects. Therefore our results provide an interesting counterpoint to the considerable evidence on the informational role of order flow found in studies such as Evans and Lyons (2005) and Rime et al (2007).

Generally, the issue of time-of-day effect on returns has received more attention in equity markets (see for example Harris (1986), Smirlock and Starks (1986) and Yadav and Pope (1992)). This is slightly surprising given the comparatively short trading hours and less promising results found in this market. These studies do not consistently find a strong intraday pattern in equity markets except perhaps for lower returns toward the end of the trading day. It is also worth noting that whereas the literature in FX markets has focussed in the information effect of order flow, its liquidity effect has received considerable attention in equity markets with increasing evidence that liquidity effects have a significant impact on equity returns in the short run (see for example Chordia et al. (2002)).

As noted above, two papers have documented the time-of-day pattern in FX returns. The first, Cornett et al (1995) study hourly data for US trading hours of FX futures from the IMM market for the period 1977 to 1991. Looking at the Deutsche Mark, British Pound, Swiss Franc, Japanese Yen and Canadian Dollar all against the US dollar they find a significant tendency for the foreign currency to rise during US trading hours with the majority of that rise occurring in the first and last two hours of trading. They also found that the foreign currency had a significant tendency to fall outside US trading hours such that the overall daily returns had no significant pattern. More recently, Ranaldo (2006) uses indicative quotes from the FX spot market to construct hourly data across the whole 24-hour trading period (excluding major holidays and weekends). The paper focuses on the Deutsche Mark (Euro), Swiss Franc, and Japanese Yen against the US dollar as well as Deutsche Mark (Euro) against the Yen over the period 1993 to 2005 and also finds a statistically significant tendency for the domestic currency to depreciate in its own trading hours.

In this paper we look in more detail at the phenomenon over the period 1997 to 2007 using data on FX spot rates and order flow from EBS – the main interdealer electronic broker for the major currencies. This EBS data gives us two important advantages over the two studies described above. First, EBS gives data on firm bid and offer prices allowing us to measure precisely the potential trading profits (for an member of the interdealer market trading at normal market size) from strategies that exploit the predictable intraday pattern discussed above. Second, our dataset also offers information on trades executed through EBS allowing us to track a significant portion of total order flow in the market. We then supplement this data with more detailed data from a single market maker that allows us to identify both the type and geographical location of order flow on intraday order flow. Our approach is entirely empirical and we favour simple models throughout though the phenomena we discuss here could in principle be modelled as some form of rational inattention perhaps incorporating time-dependence and observation costs such as in Abel, Eberly and Panageas (2009).

Overall, we find significant time-of-day effects in the returns of all the currencies we investigate that are consistently related to depreciation in local trading hours. We also find the same pattern in order flow suggesting that it is the tendency of local market participants to be net purchasers of foreign exchange in their own trading hours that is responsible for this phenomenon. This result is corroborated by market maker data

The rest of this paper is organised as follows. Section 2 describes our data and the statistical properties of the time-of-day effect. Section 3 looks at trading profits from simple time-of-day based trading rules while section 4 investigates whether this pattern is related to FX order flow. Section 5 offers more insight on this phenomenon from more detailed data provided by a single market maker and capital flow data. Section 6 concludes.

2 Data and time-of-day effects

2.1 Data

We employ a detailed transactions data set for the period 1997 to 2007 from EBS who are the dominant electronic broker for all but two of the FX crosses which we analyse in this paper (see table). Along with Reuters, the EBS electronic order book has now effectively displaced voice brokers and direct dealing between traders. In practice EBS has become dominate in the major currency pairs (EUR/USD and USD/JPY) while Reuters dominates in most of the minor crosses. We focus on six crosses (EUR/USD, USD/JPY, GBP/USD, EUR/JPY, USD/CHF and AUD/USD) in order to give a give results for a range of different time zones while focussing on the major crosses in which EBS is dominant.

Table 1: EBS Transactions Data Summary Statistics

	EUR/USD	USD/JPY	GBP/USD	EUR/JPY	USD/CHF	AUD/USD
EBS share of electronic	81%	95%	7%	99%	99%	1%
Electronic share of total	54%	50%	54%	57%	47%	43%
EBS share of total	44%	48%	4%	57%	47%	1%
Average Trade Size	4.49m	3.87m	3.57m	4.01m	3.70m	3.55m
Average Bid-Ask Spread	0.017%	0.018%	0.056%	0.060%	0.072%	0.055%

This table presents summary statistics for our sample of EBS turnover data. We show estimates of EBS share of electronic interdealer trading and overall FX turnover. We also show average trade size (2000-2007) and average bid ask spread (1997-2007) for all active trading hours (i.e. hours in which at least one trade took place). The share of electronic interdealer broking is derived from a comparable sample of EBS and Reuters Dealing-2002 (the other electronic interdealer broking platform) from August 2000 to January 2001 (see Breedon and Vitale (2004)). Overall market share is estimated from the 1998, 2001, 2004 and 2007 BIS surveys by assuming that all trading between reporting dealers is electronic. This is likely to be an over estimate at the start of the sample (as other trading methods were used) but an under estimate at the end of the sample (as EBS is now being used by some customers such as Hedge Funds).

Over the whole sample 2/1/1997 to 1/6/2007 we have the number of customer initiated buy and sells and the price at which each trade was undertaken. We define the working time from Monday 00:00 to Friday 24:00 GMT. However, in the case of JPY and

AUD, the week is extended it from Saturday 18:00 GMT to Friday 24:00 GMT.[1] For the main results in this paper we include holidays except where no trading occurs whatsoever[2]. For the purposes of this paper we aggregate the transaction data into hourly data so that we work with the end hour bid and ask prices and the cumulative trades over the hour.

2.2 Time of Day effects

We begin by testing the relationship between hourly returns and the time of day for our sample of currencies. Throughout this section we define returns using the prevailing midquote price at the end of each hour. Our initial goal is to confirm the results of Cornett et al (1995) and Ranaldo (2006) that local currencies tend to depreciate in their own trading hours and to appreciate outside them and to establish any hourly patterns that contribute to that effect. Of course, as an OTC market that trades across several time zones, the foreign exchange market does not have precise trading hours though it is clear that traders in particular locations tend to operate over fairly fixed trading hours. We take futures trading hours (FX futures where possible) as our guide and then compare these opening hours with distinct increases in trading volume that occur before - and thus are unrelated to - news releases and standard fixings (and so are presumably related to the initial trading activity of local traders become active). Table 2 presents our assessment of these hours (note that the results presented below are not substantially affected by the precise choice of trading times).

Table 2: Estimated local trading hours in FX markets

Trading centre	Estimated trading hours (GMT)	Futures markets
United States	13.00-21.00	NYBOT, CME. PHLX
Europe	07.00-15.00	NYBOT(Dublin)
Japan	23.00-6.00	TIF (no FX)
Australia	23.00-6.00	ASE

We present three basic tests of the relationship between hourly returns and time of day, a simple test of significant excess returns, an excess returns test adjusted for time-varying volatility and a non-parametric sign test of returns.

[1] These definitions of working time match the main trading activity in the different world regions. Other definitions have been considered and the results remain unchanged.
[2] In particular, we checked all the tests both including and excluding periods of no transactions. This control test guarantees that all the patterns are related to the trading activity and all trading rules are tradable.

1) **Simple test of significant excess returns**. We conduct two-sample t-tests for the acceptance of the null hypothesis of equality in means. These t-statistics refer to two-tail statistics on the difference between a given intraday return mean over all the returns at the same intraday period. We perform the two-sample equal variance (homoscedastic) test.[3]

2) **Excess returns allowing for heteroscedasticity and autocorrelation**. An important drawback of a simple test of excess returns is that it does not allow for the fact that the volatility of returns varies markedly over the trading day – with volatility usually concentrated on the morning sessions of each of the currencies in a given pair. To help adjust for this effect we estimate a time of day returns model where volatility has a simple time-of-day structure. We performed GARCH regressions as follows:

$$r_{t,i} = \sum_{h=1}^{24} \alpha_h . d_h + \sum_{k=1}^{k} \rho_h . r_{t,i-k} + \varepsilon_{t,i} \tag{1}$$

$$\sigma_{t,i}^2 = \sum_{h=1}^{24} \omega_h d_h + \theta \varepsilon_{t,i-1}^2 + \lambda \sigma_{t,i-1}^2 \tag{2}$$

Where $r_{t,i}$ is the log change of the exchange rate from hour i -1 to i on day t, d_h is a dummy variable equal one at hour h and 0 otherwise, $\varepsilon_{t,i}$ is the residual and α, β as well as ρ are parameters. The conditional variance $\sigma_{t,i}^2$ of the error term is defined in equation 2 in which ω is the constant, θ and λ are parameters. This GARCH model accounts for three main statistical characteristics of the time series of intraday returns: autocorrelation, heteroscedasticity and non-Gaussian errors. This model lends itself for several further specifications. In particular, we also analysed a Moving Average instead of Auto-Regressive specification.

3) **Sign test.** As a simple non-parametric test of the properties of hourly returns we also assess the probability of observing positive returns in a given hour and test the significance of that probability using a binomial distribution (we also conducted the Wilcoxon signed ranks test – results available from the authors).

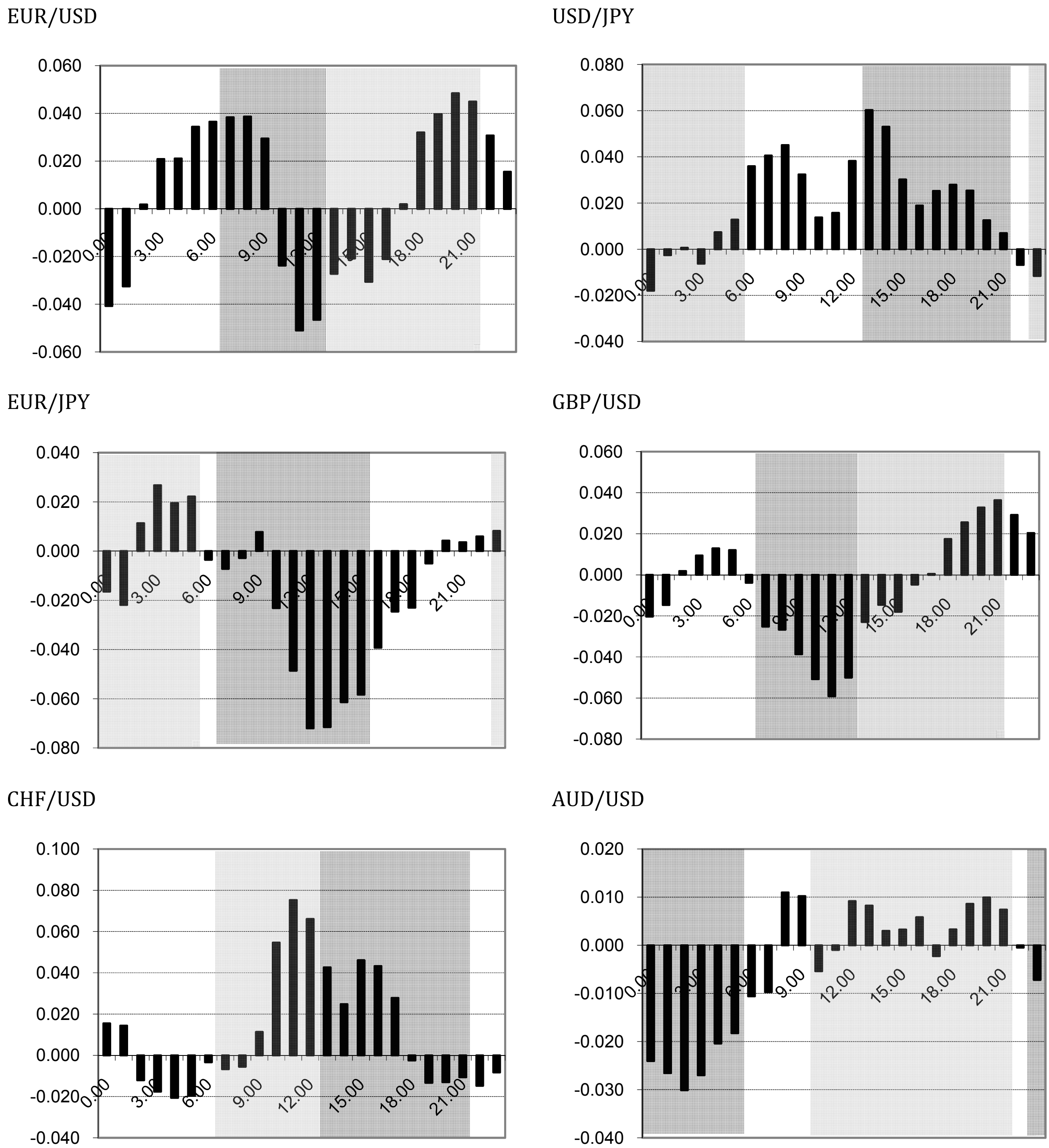
[3] The homoscedastic t-test is a stricter test than the heteroscedastic case. In fact, the probability associated with a Student's t-test for equality in means has an upward bias and leads to a more likely rejection of the inequality hypothesis.

Table 3: Statistical Properties of Hourly FX Returns

Time (GMT)	EUR/USD Simple	EUR/USD GARCH	EUR/USD Sign	USD/JPY Simple	USD/JPY GARCH	USD/JPY Sign	EUR/JPY Simple	EUR/JPY GARCH	EUR/JPY Sign
1.00	-0.041**	0.000	0.415**	0.018*	0.000	0.523*	-0.016*	0.000	0.482
2.00	0.008	-0.034**	0.531**	-0.015*	0.019*	0.459**	-0.005	-0.010	0.463**
3.00	0.034**	0.014**	0.591**	-0.003	-0.021*	0.483*	0.033**	-0.004	0.559**
4.00	0.019*	0.064**	0.567**	0.007	-0.014*	0.505	0.015	0.038**	0.551**
5.00	0.000	0.017**	0.480*	-0.014	0.003	0.485	-0.007	0.022**	0.475*
6.00	0.013	-0.002	0.526*	-0.005	-0.008	0.483*	0.003	-0.004	0.498
7.00	0.002	0.016**	0.500	-0.023**	-0.007	0.460**	-0.026**	0.006	0.464**
8.00	0.002	0.005	0.487	-0.005	-0.020**	0.495	-0.004	-0.014	0.494
9.00	0.000	0.002	0.500	-0.005	0.001	0.509	0.004	-0.003	0.518*
10.00	-0.009	0.001	0.476*	0.013	0.009	0.524*	0.011	0.009	0.506
11.00	-0.053**	-0.004	0.403**	0.019*	0.020**	0.536**	-0.031**	0.015	0.448**
12.00	-0.027**	-0.049**	0.448**	-0.002	0.025**	0.492	-0.025**	-0.022**	0.463**
13.00	0.005	-0.030**	0.496	-0.023**	0.010	0.478*	-0.023**	-0.028**	0.475*
14.00	0.019*	0.006	0.510	-0.022**	-0.031*	0.479*	0.000	-0.029**	0.502
15.00	0.006	0.019*	0.511	0.007	-0.014	0.502	0.010	0.002	0.509
16.00	-0.010	0.010	0.507	0.023**	0.016	0.523*	0.003	0.018	0.528**
17.00	0.009	-0.005	0.516	0.011	0.035**	0.516	0.019*	0.023*	0.518*
18.00	0.023**	0.000	0.530**	-0.006	0.013*	0.493	0.015	0.022**	0.530**
19.00	0.030**	0.023**	0.542**	-0.003	-0.009	0.487	0.002	0.025**	0.493
20.00	0.008	0.037**	0.526*	0.002	-0.012*	0.503	0.018*	0.009	0.524*
21.00	0.009	0.005	0.521*	0.013	0.003	0.530**	0.009	0.003	0.523*
22.00	-0.004	0.011*	0.499	0.006	0.013**	0.500	-0.001	0.011*	0.490
23.00	-0.014*	-0.002	0.460**	0.014	-0.002	0.518*	0.002	-0.005	0.488
00.00	-0.015*	-0.018*	0.459**	0.005	0.015**	0.513	0.002	0.005	0.493

Time (GMT)	GBP/USD Simple	GBP/USD GARCH	GBP/USD Sign	CHF/USD Simple	CHF/USD GARCH	CHF/USD Sign	AUD/USD Simple	AUD/USD GARCH	AUD/USD Sign
1.00	-0.020**	0.000	0.458**	0.015*	0.000	0.524**	-0.024**	0.000	0.439**
2.00	0.006	-0.023**	0.512	-0.001	0.020**	0.484*	-0.003	-0.025**	0.512
3.00	0.016**	-0.001	0.569**	-0.026**	-0.004	0.461**	-0.004	-0.001	0.513
4.00	0.008	0.018**	0.539**	-0.006	-0.027**	0.473**	0.003	-0.004	0.533*
5.00	0.003	0.007	0.495	-0.003	-0.013**	0.498	0.007	0.004	0.533*
6.00	-0.001	0.004	0.489	0.001	-0.001	0.505	0.002	0.010	0.511
7.00	-0.016**	-0.002	0.475*	0.016*	0.002	0.512	0.008	0.002	0.550**
8.00	-0.021**	-0.017**	0.474**	-0.003	0.014*	0.503	0.001	0.004	0.500
9.00	-0.002	-0.022**	0.494	0.001	0.002	0.506	0.021*	0.002	0.510
10.00	-0.012*	-0.003	0.482*	0.017*	0.006	0.526**	-0.001	0.023*	0.461*
11.00	-0.012*	-0.011	0.477*	0.043**	0.020*	0.580**	-0.016	0.004	0.459**
12.00	-0.008	-0.005	0.488	0.021**	0.050**	0.538**	0.004	-0.016	0.487
13.00	0.009	-0.011	0.500	-0.009	0.026**	0.497	0.010	0.004	0.516
14.00	0.027**	0.011	0.518*	-0.023**	-0.010	0.471**	-0.001	0.014	0.507
15.00	0.008	0.028**	0.508	-0.018*	-0.020*	0.487	-0.005	-0.004	0.498
16.00	-0.003	0.020*	0.498	0.021**	-0.016	0.520*	0.000	-0.010	0.525
17.00	0.013*	-0.002	0.513	-0.003	0.003	0.494	0.003	0.002	0.504
18.00	0.005	0.015*	0.506	-0.015*	-0.013	0.474**	-0.008	0.004	0.476
19.00	0.017**	0.016*	0.542**	-0.030**	-0.019*	0.461**	0.006	-0.008	0.538*
20.00	0.008	0.020**	0.511	-0.011	-0.028**	0.478*	0.005	0.006	0.524
21.00	0.007	0.012*	0.517	0.000	-0.014*	0.510	0.001	0.008	0.493
22.00	0.004	0.010**	0.506	0.002	0.005	0.489	-0.003	0.001	0.430**
23.00	-0.007	0.002	0.448**	-0.004	-0.002	0.499	-0.008	-0.002	0.470
00.00	-0.009	-0.009**	0.469*	0.006	0.002	0.511	-0.007	-0.007	0.491

Figure 1: Cumulative Returns over average day (GMT)



Dark shading indicates local trading hours for base currency, light shading indicates local trading hours for term currency

Table 3 presents evidence that hourly FX returns do seem to follow significant time of day patterns, (see figure 1 for a visual representation) which, as predicted, pattern show that local currencies tend to depreciate during their own trading hours. Table 4 tests the trading hours phenomenon more precisely by conducting our tests on opening-to-closing or opening-to-opening (for the cases when the opening session of one side of the currency pair occurs whilst the first market is still open – as in the case of EUR/USD)

Table 4: Statistical Properties of trading day returns

	Time Period	Average Return	Share Positive
EUR/USD	7.00-13.00	-0.084**	0.44**
	13.00-21.00	0.100**	0.53**
USD/JPY	23.00-6.00	0.017**	0.51
	13.00-21.00	0.000	0.5
EUR/JPY	7.00-15.00	.029**	0.52
	23.00-6.00	-0.057**	0.48**
GBP/USD	7.00-13.00	-0.071**	0.45**
	13.00-21.00	0.092**	0.55**
USD/CHF	13.00-21.00	0.095**	0.56**
	7.00-13.00	-0.088**	0.48
AUD/USD	23.00-6.00	-0.028**	0.50
	13.00-21.00	0.016**	0.52**

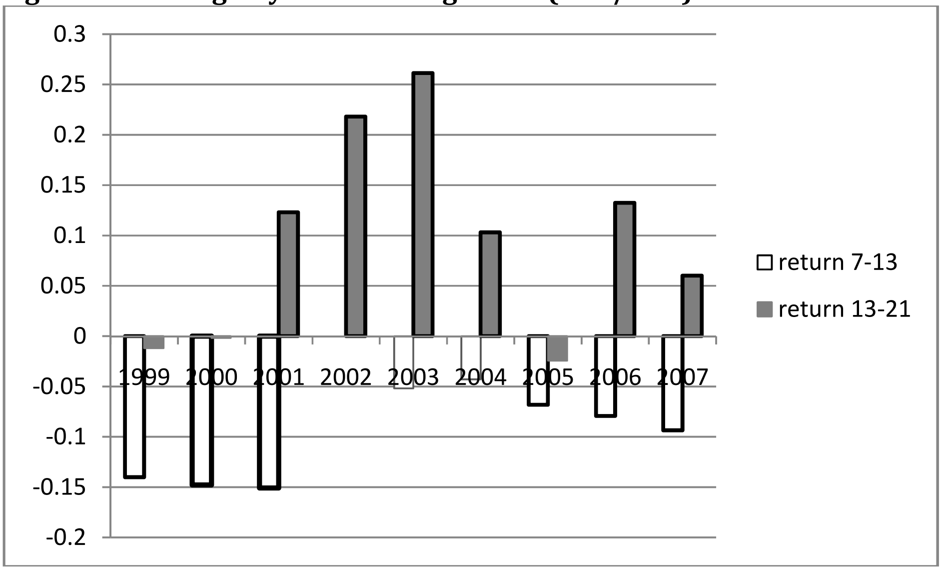
** indicate statistical significance at the 5% level

With the partial exception of USD/JPY the time-of-day pattern is of the predicted sign and is significant (when looking at returns). Although not all the sign tests are individually conclusive the pattern of probabilities is quite convincing.

2.3 Stability through time

Since the time-of-day phenomenon was first documented some years ago (Cornett et al (1995)), it is possible that its impact has diminished more recently. Figure 2 shows the significance of the EUR/USD trading day effect through time by estimating average returns over the European and US trading sessions year by year. Interestingly, although the returns over each session individually show considerable variation, the difference in returns between the two sessions remains remarkably stable. We find similar results for the other currency pairs.

Figure 2: Trading Day effect through time (EUR/USD)



Annualised return at the end of the year from 7:00 to 12:59 GMT (white bars) and from 13:00 to 22:59 GMT (grey bars) on EUR/USD. Solid borders indicate returns significant at 5% level.

3 Trading Returns

In section 2 we saw that there is a statistically significant time-of-day effect in foreign exchange returns related to local trading hours. In this section we assess the extent to which these effects can generate profitable trading strategies. Thus in this section we measure returns using bid and ask prices rather than the midquotes used in section 2 (recall that on EBS the quoted bid and ask prices are firm and thus could be transacted at normal size by the interdealer community).

Table 5: Trading Returns from a basic trading day strategy

	Time period	**Average return**
EUR/USD	Short 7.00-13.00	0.06%
	Long 13.00-21.00	0.07%
USD/JPY	Long 23.00-6.00	-0.13%
	Short 13.00-21.00	-0.05%
EUR/JPY	Short 7.00-15.00	-0.05%
	Long 23.00-6.00	-0.42%
GBP/USD	Short 7.00-13.00	-0.12%
	Long 13.00-21.00	-0.08%
USD/CHF	Long 13.00-21.00	-0.08%
	Short 7.00-13.00	-0.02%
AUD/USD	Short 23.00-6.00	-0.51%
	Long 13.00-21.00	-0.50%

Table 5 shows the returns from a simple open-to-close/open-to-open trading strategy. As might be expected, most of these simple time-of-day trading strategies are not profitable when trading costs are included. However, the notable exception is EUR/USD where the significant intraday pattern combined with narrow spreads in this cross means that this basic strategy has been profitable on average with Sharpe Ratios of 1.3 and 0.9 respectively for the morning short and afternoon long. This result is even more surprising when one considers that we have made no allowance for bank holidays or other simple adjustments that could presumably improve returns[4].

4 Time of day effects and Order Flow

In sections 2 and 3 we saw that all the currencies in our sample displayed a significant tendency to depreciate in local trading hours and that in the case of EUR/USD this tendency could be exploited to generate trading profits. In this section we explore the relationship of this effect to order flow.

4.1 Time of day effects in FX order flow

Table 6 repeats the time-of-day analysis described above but this time for order flow. Once again we see a tendency for local currency selling to occur in local trading hours. As a result we tend to see a strong relationship between hourly order flow and hourly returns (Figure 3) that is statistically significant in all cases.

This result suggests that it is the timing of trades that is largely responsible for the hourly pattern in returns. A plausible explanation for this pattern of order flow (which we discuss further below) is that international investment funds tend to conduct currency trades in their own trading hours and that since they tend to receive net inflows of domestic currency this implies a bias against the local currency in domestic trading hours. Additionally, Cornett et al (1995) highlight currency of invoicing effects that lead importers to be net demanders of foreign currency rather than exporters as imports are more commonly invoiced in foreign currency, once again the tendency of these trades to be conducted in local trading hours gives the pattern we observe here.

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[4] Bank Holiday effects seem quite powerful in practice. For example, the dollar has appreciated against the Euro (or DM) on July 4th in 14 of the last 19 occasions. This is presumably due to the absence of US-based order flow on that day.

Table 6: Statistical Properties of Hourly Order Flow

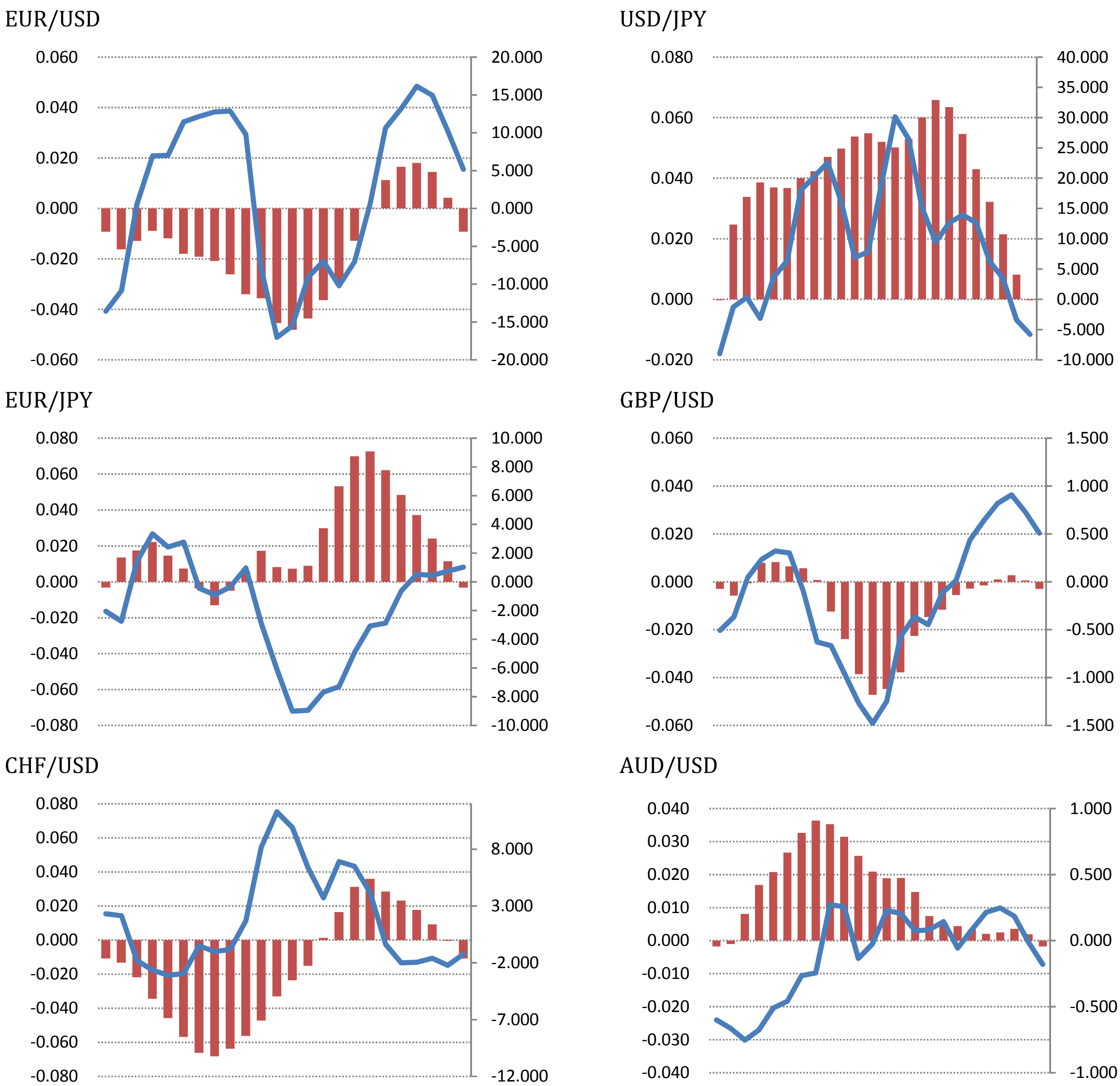
	EUR/USD		USD/JPY		EUR/JPY	
	Average	Sign	Average	Sign	Average	Sign
1.00	-3.067**	0.467**	-0.164**	0.523*	-0.396**	0.542**
2.00	-2.341	0.541**	12.506**	0.459**	2.097	0.511
3.00	1.116*	0.558**	4.591**	0.483*	0.486	0.542**
4.00	1.336	0.536**	2.356	0.505	0.595*	0.510
5.00	-0.994**	0.491	-0.831	0.485	-0.951	0.506
6.00	-2.050	0.512	-0.077**	0.483*	-0.909**	0.489
7.00	-0.366	0.488	1.637*	0.460**	-1.391*	0.478*
8.00	-0.563*	0.473*	1.145**	0.495	-1.165*	0.496
9.00	-1.777**	0.443**	2.368**	0.509	1.016**	0.504
10.00	-2.636	0.476*	1.371**	0.524*	1.320**	0.500
11.00	-0.519**	0.448**	1.986	0.536**	1.466*	0.478*
12.00	-3.268	0.481*	0.536*	0.492	-1.135	0.477*
13.00	-0.901*	0.497	-1.421	0.478*	-0.121	0.487
14.00	1.495**	0.492	-0.923**	0.479*	0.206**	0.521*
15.00	2.412**	0.492	1.403**	0.502	2.611**	0.524*
16.00	2.456**	0.524*	3.542**	0.523*	2.930**	0.525*
17.00	5.399**	0.534**	2.899	0.516	2.088	0.504
18.00	4.391**	0.570**	-1.191**	0.493	0.335*	0.475*
19.00	3.618**	0.542**	-4.415**	0.487	-1.310**	0.471**
20.00	1.781	0.527*	-5.841**	0.503	-1.720**	0.494
21.00	0.486	0.514	-5.366**	0.530**	-1.399**	0.495
22.00	-1.171**	0.472**	-5.393**	0.500	-1.648**	0.485
23.00	-3.428**	0.445**	-6.642**	0.518*	-1.570**	0.491
00.00	-4.477**	0.470**	-4.241	0.513	-1.832	0.493
	GBP/USD		**CHF/USD**		**AUD/USD**	
	Average	**Sign**	**Average**	**Sign**	**Average**	**Sign**
1.00	-0.074	0.498	-1.614	0.530**	-0.043	0.509
2.00	-0.070	0.530*	-0.373**	0.482*	0.018**	0.558**
3.00	0.130*	0.549**	-1.286**	0.449**	0.228**	0.582**
4.00	0.214	0.525*	-1.890**	0.454**	0.219	0.540*
5.00	0.007	0.499	-1.708**	0.478*	0.099*	0.547*
6.00	-0.045	0.496	-1.656**	0.489	0.148*	0.530
7.00	-0.018	0.479*	-1.401	0.512	0.148	0.514
8.00	-0.124**	0.468**	-0.300*	0.510	0.094	0.480
9.00	-0.329*	0.485	0.666**	0.512	-0.028	0.489
10.00	-0.286**	0.483	1.126**	0.525**	-0.095*	0.471
11.00	-0.367	0.487	1.353**	0.555**	-0.144*	0.481
12.00	-0.216	0.491	2.136**	0.526**	-0.120	0.500
13.00	0.062	0.505	1.403**	0.515	-0.050	0.508
14.00	0.173**	0.523*	1.280**	0.519*	0.003	0.459*
15.00	0.380	0.510	2.472**	0.511	-0.106**	0.463*
16.00	0.199	0.501	2.271**	0.509	-0.182	0.505
17.00	0.076	0.515	2.221*	0.502	-0.052	0.471
18.00	0.152	0.502	0.694**	0.475*	-0.025	0.514
19.00	0.067	0.516	-1.118*	0.474**	-0.026	0.470
20.00	0.034	0.505	-0.798*	0.483*	-0.033	0.478
21.00	0.062	0.510	-0.819**	0.492	0.012	0.518
22.00	0.044	0.464*	-1.272**	0.490	0.026	0.414**
23.00	-0.054	0.455*	-1.448**	0.486	-0.041	0.425**
00.00	-0.089	0.449**	-1.551**	0.494	-0.092	0.499

Average: average order flow on hourly basis and related tstat for equality in means (** significance at 1%, * significance at 5% level) Sign: Proportion of positive order flow and binomial test (** significance at 1%, * significance at 5% level)

4.2 The order flow returns relationship

As the previous tables and Figure 2 show, both FX returns and order flow seem to display a similar intraday pattern, in this section we test to see if pattern in order flow can explain the pattern in returns.

Figure 2: Cumulative order flow and returns on average day (GMT)



(Columns = order flow (RHS), line = returns (LHS))

To do this we employ the simple bivariate VAR model of order flow and returns proposed by Hasbrouck (1991) where returns are a function of contemparenous order flow and lags of both order flow and returns whilst order flow is a function of lagged returns and order flow. Although this model has been criticized both for assuming that contemporaneous returns do not influence order flow and for not allowing for any cointegrating relationship between cumulative order flow and the asset price (see for example, Love and Payne (2006)) it is adequate for our purpose since we simply require a straightforward framework in which to analyse the intraday pattern of order flow and returns. Table 7 shows the estimates of our VARs isolating both the contemporaneous and lagged impact of order flow on returns. Lag lengths were chosen according to the Schwarz criterion (generally 3 lags) though only the cumulative coefficient and a joint test of significant for all lags are shown in the Table.

Focusing on the return equation (which is the key one for our analysis) we see a similar pattern across all currencies with a significantly positive contemporaneous impact of order flow on returns and a significantly negative – though smaller - lagged impact.

Table 7: Estimates of Returns Order flow relationship (order flow /10000)

	Return equation	Coeff	t-Statistic	Order flow equation	Coeff	t-Statistic
AUDUSD	Return Lagged	-0.013	-2.836	Return Lagged	-0.023	-25.306
	OF	0.481	21.392			
	OF lagged	-0.481	-20.993	OF lagged	0.300	230.555
	Adj. R-sq.	0.010		Adj. R-sq.	0.060	
USDCHF	Return Lagged	-0.069	-20.575	Return Lagged	-0.278	-66.084
	OF	0.276	97.534			
	OF lagged	-0.020	-6.638	OF lagged	0.159	41.031
	Adj. R-sq.	0.090		Adj. R-sq.	0.028	
EURJPY	Return Lagged	-0.127	-35.275	Return Lagged	-0.108	-17.166
	OF	0.327	162.137			
	OF lagged	-0.006	-2.448	OF lagged	0.183	41.177
	Adj. R-sq.	0.238		Adj. R-sq.	0.016	
EURUSD	Return Lagged	-0.088	-28.188	Return Lagged	-0.680	-70.633
	OF	0.028	22.220			
	OF lagged	-0.008	-6.195	OF lagged	0.201	46.988
	Adj. R-sq.	0.010		Adj. R-sq.	0.063	
GBPUSD	Return Lagged	-0.086	-24.152	Return Lagged	-0.039	-19.844
	OF	0.399	57.898			
	OF lagged	-0.022	-3.169	OF lagged	0.171	43.533
	Adj. R-sq.	0.042		Adj. R-sq.	0.014	
USDJPY	Return Lagged	0.053	15.808	Return Lagged	-0.543	-66.427
	OF	0.224	155.318			
	OF lagged	-0.047	-28.221	OF lagged	0.171	40.937
	Adj. R-sq.	0.188		Adj. R-sq.	0.029	

Using these VARs we can investigate if the intraday pattern in returns described above can be explained by order flow (note that we have already tested to see if autocorrelation in returns can explain this effect so the inclusion of lagged returns is unimportant). The simplest way to do this is to see if the significant intraday pattern is still present after allowing for the impact of order flow on returns (i.e. is the intraday pattern present in the residuals on the returns equation. Table 8 presents the results of this test.

Table 8: Intraday patterns in order flow adjusted returns

	Time Period	Average Return	t-Stat	Prob t-Stat
EUR/USD	7.00-13.00	0.0098	-0.0385	0.9693
	13.00-21.00	0.0004	0.0733	0.9416
USD/JPY	23.00-6.00	0.0003	0.0790	0.9370
	13.00-21.00	0.0003	0.0621	0.9505
EUR/JPY	7.00-15.00	-0.0006	-0.1317	0.8953
	23.00-6.00	0.0001	0.0481	0.9616
GBP/USD	7.00-13.00	-0.0001	0.4000	0.6892
	13.00-21.00	0.0004	0.0733	0.9416
USD/CHF	13.00-21.00	-0.0002	-0.0323	0.9742
	7.00-13.00	-0.0005	-0.0861	0.9314
AUD/USD	23.00-6.00	-0.0002	-0.0002	0.9999
	13.00-21.00	0.0000	0.0082	0.9935

The results are clear, after allowing for order flow there appears to be no residual intraday pattern in returns. This confirms that the intraday pattern in returns and order flows are strongly related and suggests that it is the intraday pattern in order flow that is driving the pattern in returns.

5 Further Evidence on Order Flow

Although order flow data from EBS gives us an excellent coverage of the interbank market, the dataset we have gives us no information on the geographical location or identity of the counterparties, it is also unclear if order flow from this source has any correspondence with macroeconomic data on capital flows. In this section we look at data from a single market maker and from detailed US capital flow data to address these limitations.

5.1 Data from a single market maker

We are lucky to have access to order flow data from BNP Paribas on both the geographical location and type of customer orders. Paribas have kindly supplied us with data on the size, sign and counterparty type and geographical location of all their customer trades over the period January 2005 to May 2007. Alhough not a key market maker, BNP Paribas is estimated to be one of the top 15 market makers (in terms of market share) for corporations, banks and real money accounts(with estimated market shares of 3.1%, 2.9% and 1.4% respectively), though not for leveraged funds (Euromoney FX poll 2008).

Table 6 shows a more detailed analysis of order flow ([buys-sells]/[buys+sells]) in different trading periods by different location of customer. Here we see the expected pattern whereby local customers tend to be net sellers of the local currency in local trading hours, though this effect is only statistically significant in a few cases. The strongest results are for USD/JPY where both US and Asian imbalances are significant, this is slightly surprising given the mixed results we obtained for USD/JPY with EBS data. The only two exceptions to the selling in local hours pattern are GBP/USD and USD/CHF in European trading hours. However, this may be due to flows from other European countries into these currencies.

Table 6: Average Order Flow imbalance in local trading hours: BNP Paribas data

	EUR/USD	USD/JPY	EUR/JPY	GBP/USD	USD/CHF	AUD/USD
European-based	-1.7%		-1.5%	+0.3%	-1.0%	
US-based	0.1%	-3.1%*		+1.7%	-1.7%	+0.7%
Asia/Australasia-based		6.8%*	3.8%*			-4.0%*

Order flow imbalance = (buys-sells)/(buys+sells) is for customers of a given geographic location in their own trading hours. * indicates that imbalance is statistically significant at the 5% level based on a difference in means test versus mean imbalance of aggregate order flow over whole trading day

Further analysis by type of customer shows that Banks and Investment Funds have the strongest tendency to sell their own currency in local trading hours while this effect is not observed in trades by corporations (though the sample of such trades is small). This suggests that the time-of-day pattern in order flow is certainly not restricted to currency of invoicing effects as implied by Cornett et al (1995).

5.2 Data from the Treasury International Capital System

Although the intra-day effect we have identified is clearly a microstructure phenomenon, it is interesting to see if we can find some correspondence between the results we have found here and macroeconomic capital flow data. Data from the US TIC system allows us to look in some detail at flows by geographic source and so make some general observations. We use the TIC data on equity flows (which are the most likely to involve an outright currency exposure) to check two propositions

1) Is it the case that US investors tend to be net purchasers of foreign equity and vice versa as our Paribas data suggest?
2) Are the intra-day patterns we have identified correlated with measured flows at the macro level? More precisely, is the average fall in the dollar in US hours over each month correlated with the recorded net purchase of foreign equity by US citizens over that month (and vice versa for flows into the US)?

Table 7 summarises our results using TIC data. It confirms that local investors tend to be net purchasers of foreign asset as we expected and that the intraday pattern is generally correlated with the scale of these net purchases (significantly so in the case of EUR/USD and AUD/USD).

Table 7: Evidence from US cross-border equity flow data

	EUR/USD	USD/JPY	GBP/USD	USD/CHF	AUD/USD
Average Net Purchases of US equity by foreigners (% of holdings, AR)	6.0%	1.9%	14.3%	3.1%	2.1%
Average Net Purchases of foreign equity by US (% of holdings, AR)	0.1%	6.3%	4.2%	0.3%	3.4%
Correlation of return in US time with US purchases	0.13*	0.04	0.11	0.10	0.09
Correlation of return in foreign time with foreign purchases	0.18**	0.06	-0.03	0.07	0.18**

Average net purchases shows average net purchases by country X of US equity(or US purchases of country X equity) as a percentage of estimated average holdings of US equity by country X (or holding of country X equity by the US) Correlation of average mid-quote return from intraday strategy with net equity purchases that month. *,** indicates significance at 10% and 5% level respectively. All flow and stock data from TIC

6 Conclusion

Despite the staggering level of turnover in FX markets, the results reported in this paper appear to confirm the growing evidence that liquidity effects are an important driver of FX returns, even when order flow is predictable. In our case it seems that the understandable tendency for market participants to trade in their own trading hours coupled with their apparent tendency to be net purchasers of foreign exchange is enough to lead to a significant and predictable pattern in order flow and FX returns. Remarkably, even the simplest trading rule associated with this pattern appears profitable in the case of EUR/USD suggesting that market makers feel the risk involved in holding intraday positions is significant. Data from an admittedly minor market maker gives support to the idea that the patterns in returns and order flow seem to have a geographic source.

Overall our results not only confirm the importance of order flow in determining FX returns, but suggest that the role of liquidity effects should not be ignored in modelling the order flow FX returns relationship

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