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The Flows of the Pacific: Asian foreign exchange markets through tranquility and turbulence*

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Abstract

Using the longest data set on FX order flow to date, along with the broadest coverage of currencies to date, we examine the effect of FX order flow on exchange rates across small and large currencies, currencies with floating or fixed regimes, and across both tranquil and turbulent periods. Over our 15 years of data for eleven Asian and Australasian currencies, we find that order flow has a potentially strong impact on all exchange rates in the sample. The effect is strongest on floating exchange rates, both economically and statistically, but is sizeable also on the other exchange rates, especially during periods of turbulence. By creating a measure of regional order flow, we show that all exchange rates depreciate as flows are moved out of Asia/Australasia and into US dollars. This is true both across regimes and if their own flow is not included in the structure of the regional flow.

JEL: F31, G01, G15
Keywords: Order flow, microstructure, Asian and Australasian exchange rates, financial crises

1 Introduction

Exchange rate movements have proven notoriously difficult to explain using macroeconomic fundamentals, leading Obstfeld and Rogoff (2001) to coin the term "exchange rate disconnect puzzle." Several financial crises over the past two decades have not made the problem any easier to solve. The ERM crisis in Europe in the

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early 1990s was followed by the Mexican peso crisis in the mid-1990s, the Asian crisis and the Russian sequel in the late 1990s, the bursting of the dot-com bubble together with crises in both Turkey and Argentina at the beginning of the new century, the global financial crisis of 2007–2009 and the current sovereign debt crisis in Europe. These crises affected different economies to different degrees, but no economy was unaffected.

In response to the lack of a plausible explanation for what drives exchange rates, researchers have begun to take a new approach that focuses on the potential implications of heterogeneity among market participants.[1] Such heterogeneity has often been suggested as a key ingredient in explaining both the disconnect between fundamentals and asset prices in general and the occurrence of financial crises.

This approach, when applied to foreign exchange (FX) markets, is often called the microstructure approach to FX and was pioneered by Evans and Lyons in a series of papers.[2] The results so far are astonishing in that their key variable, net buying pressure for currency (or order flow), appears to be a key determinant of exchange rates. In some cases more than 50% of the variation in returns have been explained by variation in order flow, numbers unheard of for macroeconomic fundamentals (Evans and Lyons, 2002a,b).[3]

Order flow is defined as the net of buyer- and seller-initiated trades in foreign (base) currency, and has a positive (negative) value if there is net buying (selling) pressure by initiators. Hence, the focus is on the action of only one party to a trade, where the initiator is the one paying transaction costs to settle the trade. In microstructure theory, a link between asset price and order flow arises because the very act of being willing to pay transaction costs reveals information about trading motives. In a setting with heterogeneous investors, these trading motives may be of relevance to the price determination process. A simple example is an equity market with (some unknown) insiders, where the market maker can detect noisy signals of insider information by observing the order flow.

Under reasonable conditions for the heterogeneity of the market participants, these trades will actually occur in equilibrium, and order flow will be non-zero, as opposed to the predictions from e.g. models of symmetric information. Hence, order flow is a natural variable for capturing the heterogeneity that we hypothesize as being essential to explaining exchange rate movements. Understanding the type of heterogeneity reflected by order flow, and hence the source for its explanatory power, remains an active research area. Evans (2010) argues that order flow reflects dispersed information on shocks that originate at the micro-level (among households and firms) and that in the aggregate constitutes macroeconomic shocks. The idea is that macroeconomic variables are aggregates of decisions at the firm and household level, and due to publication lags at the aggregate level, market participants are able to learn about the macroeconomy in real time by observing the trading of firms and households. Evans finds support for this view in that the trading of Citibank's customers can be used to forecast shocks to the macroeconomy. Others, like Froot and Ramadorai (2005) and

[1]Studying implications of investor heterogeneity for asset price determination is not new, and did not originate from exchange rate economics. The approach, often labeled market microstructure, initially focused primarily on equity markets (see O'Hara, 1995).

[2]Lyons (2001) and Evans (2011) give excellent overviews of the field and its development.

[3]See Osler (2009) and Evans and Rime (2012) for overviews of the empirical literature.

Berger, Chaboud, Chernenko, Howorka, and Wright (2008), have questioned such a fundamentals-based view of the impact of order flow and believe it is due to changes in risk premiums related market clearings during portfolio shifts and liquidity disruptions. However, under both views, a positive order flow (net buying pressure on base currency) leads to an appreciation of the base currency.

One major obstacle to studying order flow has been data availability, both in terms of currencies and with respect to length of samples. In this paper, we contribute to the literature on FX microstructure in several ways. First, we examine a larger set of currencies than has hitherto been the case. We study eleven currencies from the Asian and Australasian region, covering both highly liquid currency pairs as well as less liquid pairs, and currencies under different monetary regimes. Second, to our knowledge, we have the longest data set studied in the literature, covering 15 years, including both tranquil and turbulent periods.

The eleven currencies studied, all quoted against the US dollar, are: the Australian dollar, the Hong Kong dollar, the Indian rupee, the Japanese yen, the South Korean won, the Malaysian ringgit, the New Zealand dollar, the Philippine peso, the Singapore dollar, the Thai baht and the New Taiwan dollar. Most of the previous literature has focused on major exchange rates, such as the euro, the Japanese yen and the British pound against the US dollar. To our knowledge, only a few earlier papers have studied the order flow of Asian currencies *other* than the yen.[4] Gyntelberg, Loretan, Subhanij, and Chan (2009) study almost two years of customer trading in the Thai baht, while Smyth (2009) study five years of interbank trading in the Australian dollar and the New Zealand dollar.[5] With respect to length of sample, Chinn and Moore (2011) use eight years of data on the US dollar against the euro and the Japanese yen from January 1999, and omits the Asian and Russian crises of the late 1990s.[6]

This paper uses data obtained from Reuters interdealer trading platforms. Trades in the interbank market are those between foreign exchange dealers of large banks, generally reflecting rebalancing of portfolios and risk sharing following transactions with end-customers, e.g. businesses, central banks and asset managers. The data provide us with tick-by-tick information on trades and bid-ask exchange rates in the different currency pairs. This enables us to generate reliable measures of order flow and measures of market liquidity, such as relative bid-ask spreads.

With these data in hand, we can examine whether the strong explanatory power of order flow found elsewhere in the empirical literature on FX microstructure also applies to Asian currencies in general, and to less liquid currencies in particular. Given the length of our data set, it is possible to see whether the relationship is robust to extending samples. More importantly, since the sample extends from early 1996 to the present for the majority of the currencies, we are able to study the role of order flow during periods of turbulence. This is important, because turbulent times are periods when both theory and data so far have provided us with little guidance.

[4] Ito and Hashimoto (2006), studying the Japanese yen and euro against the US dollar, provide some details on intraday patterns during Asian trading hours.

[5] Fong, Valente, and Fung (2010) is a another exception, conducting a microstructure analysis of the Hong Kong Dollar. Their focus is different however, in that they examine deviations from covered interest rate parity and its relation to liquidity.

[6] Breedon, Rime, and Vitale (2010) use ten years of data on order flow to study the forward rate bias.

We do not take a strong position in the debate on the structural reasons for any impact of order flow on exchange rates. Rather, following the approach of e.g. Chordia, Roll, and Subrahmanyam (2002), we document that the strong impact of order flow is a very robust result across levels of liquidity, both in tranquil and turbulent periods, and even across exchange rate regimes. We find a strong impact for relatively liquid currencies like the Australian dollar and the New Zealand dollar, but also for smaller currencies, some of which are under more fixed exchange rate regimes, such as the Indian rupee, the Singapore dollar, the Thai baht, the New Taiwan dollar, and the Hong Kong dollar. Although the effect is strongest both in economic and statistical terms on the floating currencies, we do find that a region-wide outflow into the US dollar creates depreciatory pressure on all eleven currencies. This includes small currencies under more fixed exchange rate regimes, such as the Malaysian ringgit and the Philippine peso, and currencies known to be subjected to relatively large and frequent interventions, such as the South Korean won. Furthermore, as expected, the effect of order flow is strongest during periods of turmoil, when market participants have the greatest need for aggregating information.

The remainder of this paper is organized as follows: Section 2 describes the FX market and our data, while section 3 presents our results using the full sample length. Section 4 describes the crises in our sample and presents the results from studying these. Section 5 concludes the paper.

2 Data and the Market

2.1 Exchange Rates

In this section we describe and discuss the different exchange rates being studied, and the data set on the interbank FX markets. Our trading data (more details below), in some cases going back to January 8, 1996, and extending to October 5, 2011, cover all major currencies of the Asia-Pacific and Australasian region except the Chinese yuan and guide us in our selection of exchange rates. Specifically, we examine the Australian dollar (AUD), the Hong Kong dollar (HKD), the Indian rupee (INR), the Japanese yen (JPY), the South Korean won (KRW), the Malaysian ringgit (MYR), the New Zealand dollar (NZD), the Philippine peso (PHP), the Singapore dollar (SGD), the Thai baht (THB) and the New Taiwan dollar (TWD), all quoted against the US dollar (USD). For all these currencies, the USD is the base currency, i.e. exchange rates are stated as foreign currency units (FCUs) per 1 USD, apart from the exchange rates of Australia and New Zealand. By foreign exchange market convention, the currency of these two Commonwealth nations is the base currency when quoted against the USD. However, for clarity of presentation, these exchange rates are also stated as FCUs per 1 USD here, i.e. the USD is treated as the base currency. For all exchange rates, we use daily closing mid-quotes obtained from Thomson Reuters Datastream.

The size of these markets may be seen in Table 1, which presents the average daily global total spot volume from the Bank for International Settlements' (BIS) 2010 triennial global survey of foreign exchange markets, together with each currency's share of this total. The combined percentage share of average daily turnover in the foreign exchange market of these eleven currencies was 33.3% as at April 2010 (BIS,

Table 1
Global Spot Volumes and Local Currency Share of Total

	1995	1998	2001	2004	2007	2010
Global	474,740	637,154	461,066	656,906	996,279	1,490,205
AUD	1.93 %	2.57 %	3.56 %	5.15 %	5.25 %	7.46 %
HKD	0.84 %	0.87 %	1.54 %	1.09 %	1.56 %	0.68 %
INR		0.08 %	0.31 %	0.46 %	0.90 %	0.58 %
JPY	22.06 %	23.58 %	26.05 %	20.86 %	20.50 %	20.15 %
KRW		0.35 %	1.48 %	1.67 %	1.51 %	1.02 %
MYR		0.02 %	0.07 %	0.06 %	0.16 %	0.28 %
NZD	0.20 %	0.16 %	0.32 %	0.79 %	1.72 %	1.32 %
PHP		0.03 %	0.05 %	0.05 %	0.13 %	0.15 %
SGD	0.42 %	2.15 %	0.71 %	0.82 %	0.84 %	1.05 %
THB		0.11 %	0.14 %	0.21 %	0.12 %	0.19 %
TWD		0.25 %	0.58 %	0.57 %	0.55 %	0.41 %

Note: The table presents the global total spot volumes, in USD millions, across all currencies against all other currencies, and across all different counterparties, corrected for local and cross-border double-counting. Each subsequent line states the share of local currency, against all other currencies, as a share of the global total. Since both currencies in a trade are counted, the sum over all currencies will be 200%. Source: *BIS Triennial Survey.*

2010).[7] Thus, almost $500 billions worth of daily transactions included one of these eleven currencies on one side. The five largest currencies (in descending order) in percentage of average total daily turnover in our sample are the JPY, the AUD, the NZD, the SGD, and the KRW, respectively. The smallest are (in descending order) the TWD, MYR and PHP.

Most of the Asian currencies in our sample were to a varying degree pegged to the US dollar prior to the Asian financial crisis of 1997. Between 1990 and 1997, the MYR moved within a 10% range of $2.7-2.5$ ringgit per USD, the THB was effectively fixed between 25.2 and 25.6 baht per USD, while the PHP fluctuated between 24 to 28 pesos per USD between 1990 and 1995 before being effectively fixed at 26.2 until 1997. The KRW followed a somewhat more flexible path, depreciating over the period 1990–97 with short periods of narrower bands, while the SGD followed a path of appreciation over the period 1990–97, taking it from a rate of 1.7 to 1.4 per USD. The TWD was under a real exchange rate targeting regime, which led to a nominal depreciation of roughly 16% between 1990 and 1997 (Corsetti, Pesenti, and Roubini, 1999).

The INR was allowed to float in 1993 after decades of being pegged to the British pound, thus joining the region's major floating currencies — the AUD, the JPY, and the NZD. The HKD, on the other hand, is the region's most rigid currency, as it is under a strict currency board regime, which effectively pegs it to the US dollar at 7.8 per USD.

In the years following the Asian financial crisis, the currencies in the sample can

[7] Because two currencies are involved in each transaction, percentage shares add up to 200% instead of 100%.

be divided into three categories according to *de jure* exchange rate policy.[8,9] Floating currencies: the AUD, the JPY, the KRW and the NZD; managed floating currencies: the INR, the MYR (since the summer of 2005), the PHP, the THB and the TWD, currencies subject to a peg/basket/band: the HKD, the MYR (prior to the summer of 2005) and the SGD.

The daily closing mid-quotes for all exchange rates are plotted in Figure 1 together with cumulative order flow (to which we return below). The periods of the Asian and Russian financial crises and the 2007–09 financial crisis are shaded in the figure. The start of the Reuters Dealing data is evident from the start of the cumulative order flow data, if later than January 8, 1996. Hence, for the INR we have transaction data from July 14, 2003, while for the KRW, the PHP, the THB and the TWD our trading data starts on September 20, 2004.

A notable increase in exchange rate volatility during periods of financial distress can be seen from Figure 1. All currencies, apart from the HKD, experience a steep depreciation relative to the US dollar during the Asian/Russian financial crises. The same pattern also holds for the 2007–09 financial crisis, except for the JPY. This effect is not surprising, given the global dominance of the US dollar as a 'safe-haven' currency in times of distress.

The case of the JPY, which can be seen in Figure 1d to actually appreciate roughly 20% over the entire course of the global financial crisis, is not surprising given the yen's dominant role as a funding currency in the carry trade. This makes the JPY appear to be a 'safe-haven' currency when uncertainty increases. The spill-over from the global financial crisis to the FX market reduced exposure to the carry trade and hence led to upward pressure on the yen as market participants sought to unwind their short yen holdings (Melvin and Taylor, 2009).

The reason that the HKD was not affected by 'a flight to liquidity' is its strict currency board regime, which in effect pegs it to the USD. The HKD can be seen to undergo a controlled depreciation against the USD in the years following the Asian financial crisis, from 7.75 to 7.8 HKD per USD.

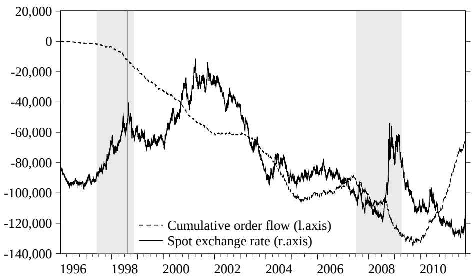
From Figure 1f it is evident that the Malaysian authorities managed to maintain the MYR's peg from the latter stages of the Asian/Russian financial crises until mid 2005. The time series properties of the MYR from Table 7 are thus somewhat surprising. However, the fluctuations in the exchange rate prior to — and after — the end of the peg, are substantial enough to reject a unit root with a p-value of 0.17 over the entire sample.

Descriptive statistics for daily annualized percentage exchange rate returns over the respective currencies' Reuters sample are povided in Table 2, panel a). On an average day, the AUD, for instance, appreciated at an annual rate of 1.58% against the USD. Given that the USD is the base currency for all exchange rates, Table 2 tells us that except for the HKD, the INR, the KRW and the MYR, all currencies on average delivered a positive daily return relative to the USD over the sample. Furthermore, the daily returns, with the notable exception of the HKD, exhibit high volatility as given

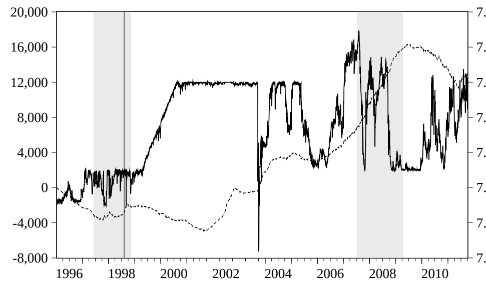
[8]This follows the various issues of the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions*, published annually.

[9]In this paper we do not go into the empirical distinction between *de jure* and *de facto* exchange rate policies. For a recent investigation of *de facto* exchange rate policies in several East Asian countries, see Kim, Kim, and Wang (2009).

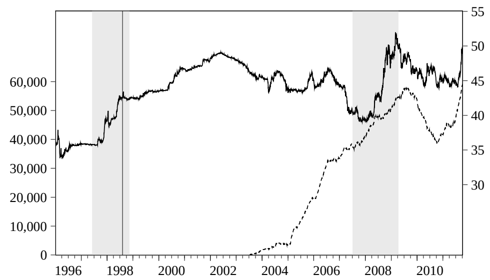
Figure 1
Exchange Rates and Cumulative Order Flow



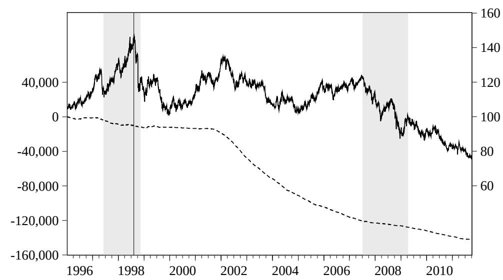
(a) Australian dollar (AUD)



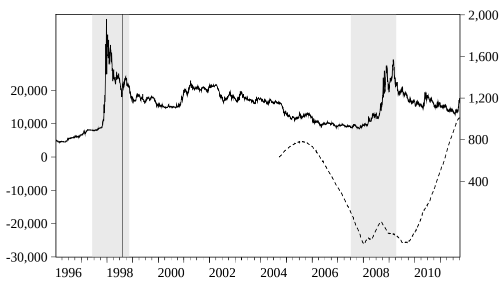
(b) Hong Kong dollar (HKD)



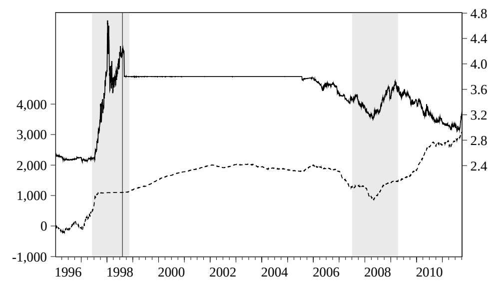
(c) Indian rupee (INR)



(d) Japanese yen (JPY)



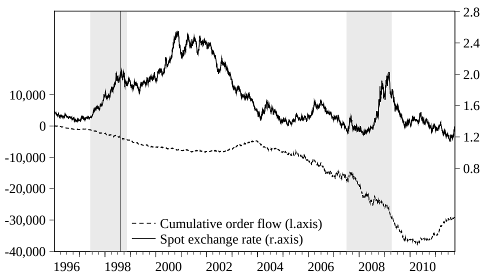
(e) Korean won (KRW)



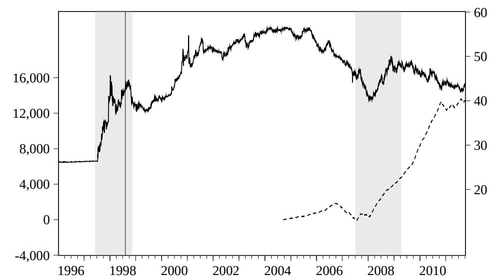
(f) Malaysian ringgit (MYR)

Note: Exchange rates are daily spot closing mid-quotes, plotted for the period 1/08/1996 – 10/05/2011 (right axis). All exchange rates are stated using the US dollar (USD) as base currency. Source: Thomson Reuters Datastream. Cumulative order flows are cumulative sums of daily order flow, plotted for each individual currency's Reuters Dealing platform sample ending 10/05/2011 (left axis). Sample details given in the text. Shading indicates the 1997–98 Asian Financial Crisis (defined as occurring between 6/01/1997 – 7/31/1998), the 1998 Russian Financial Crisis (between 8/1/1998 – 10/31/1998) and the 2007–09 Global Financial Crisis (between 7/01/2007 – 3/31/2009).

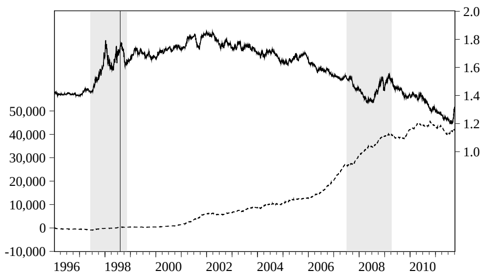
Figure 1
Exchange Rates and Cumulative Order Flow (Continued)



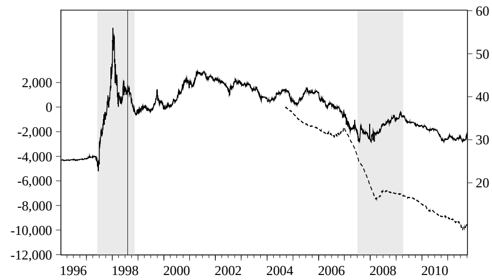
(g) New Zealand dollar (NZD)



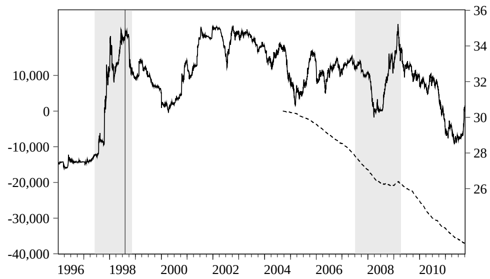
(h) Philippine peso (PHP)



(i) Singapore dollar (SGD)



(j) Thai baht (THB)



(k) New Taiwan dollar (TWD)

Note: See previous graph for details.

by their standard deviations. The result for the HKD is no surprise, given its peg. The result of lower exchange rate volatility for fixed exchange rates relative to floating exchange rates is documented by Klein and Shambaugh (2010). Moreover, all return distributions are leptokurtic, which indicates that tail risk is relatively high. The THB has the 'fattest tails' by far, which indicates the highest tail-risk of the currencies in our sample. The THB is furthermore the only currency in our sample that exhibits double digit first order autocorrelation in its daily exchange rate return. Testing the time series properties of the exchange rates reveals that they all (by usual degrees of confidence) contain a unit root, apart from USD/HKD and USD/KRW. Augmented Dickey-Fuller tests for the exchange rates are provided in Table 7 in the appendix.[10]

2.2 Trading in the Foreign Exchange Market

The FX market is predominantly an over-the-counter market, where trading is typically divided into two tiers, the interbank market and the bank-customer market. Customers are parties with the final demand for currency, while the interbank market is a very important and efficient vehicle for banks to manage and share the risk they assume when intermediating customer trades. Historically, the foreign exchange market has been decentralized, with trading spread across several locations and with several dealers providing liquidity. Furthermore, the trading process has been opaque; for example, banks are typically not required to disclose information on their trading with end-users, which they often are required to do in equity markets. If the hypothetical hedge fund *AggressiveInvest* bought x THB worth y USD billion, this is information that remains with the bank that executed the trade. The decentralized and opaque nature of trading, and the fact that banks predominantly act as intermediaries for customers and therefore desire to keep a neutral position themselves, ensure that the customer market and the interbank market are linked in important ways.[11] In case of the hypothetical hedge fund *AggressiveInvest* above, the bank in question would probably offload the volume in the same direction in the interbank market, hence ensuring that the interbank order flow reflected the customer trade.

In the interbank market, dealers can trade with each other directly in the form of bilateral trades, or trades via brokers. Nowadays both kinds of trades are primarily done electronically, the former over "chat"-like networks and the latter via electronic brokers. In the early 1990s, bilateral trades were the preferred channel, but after the introduction of electronic brokers, broker-mediated trades soon came to dominate. The dominant role of electronic brokers is more pronounced in the liquid exchange rates, while the direct channel still retain a sizeable share of trading in the less liquid currencies. The dominant platform for direct trading is the Reuters D2000-1, or Dealing Conversational as it is also called.

Electronic brokers, which match orders from screens linked together in networks

[10]Test results not reported here, show that the rejection of a unit root in the USD/KRW exchange rate does not hold when considering the sample for the Reuters-data (p-value of 0.48). This is also clear when looking at the USD/KRW exchange rate right of the vertical line in Figure 1e. The ADF-test of the USD/TWD exchange rate reported in Table 7 further shows a p-value of 0.09. Test results not reported here, show that when considering the sample for the Reuters data, this p-value rises to 0.41.

[11]Although major FX banks do proprietary speculative position-taking in FX markets, the volumes devoted to this are small compared to their intermediary liquidity providing role.

Table 2
Descriptive Statistics of Exchange Rates

	Mean	σ	$\rho(1)$	Skew.	Kurt.	p90	p10	Obs.
				a) Exchange rate return				
AUD	-1.58	213.14	-0.06	0.40	14.72	224.68	-218.56	4,075
HKD	0.04	8.15	-0.08	-2.85	60.89	6.13	-5.76	4,073
INR	0.80	107.90	-0.01	0.06	9.47	118.50	-110.26	2,123
JPY	-1.93	176.41	-0.02	-0.44	9.15	198.97	-198.12	4,075
KRW	0.48	217.48	0.07	-0.08	33.15	174.19	-173.45	1,828
MYR	1.38	137.02	0.06	0.44	60.11	71.85	-71.02	4,014
NZD	-0.94	209.70	-0.01	0.36	6.76	239.74	-233.94	4,072
PHP	-3.44	109.17	-0.08	0.19	12.97	117.87	-122.53	1,812
SGD	-0.54	94.53	-0.04	-0.20	14.22	95.36	-96.16	4,071
THB	-3.85	154.97	-0.24	0.51	123.82	94.12	-109.78	1,833
TWD	-1.37	76.82	0.02	-0.21	6.61	83.63	-88.17	1,824
				b) Relative bid-ask spreads				
AUD	4.00	1.90	0.80	3.83	67.97	6.45	2.16	4,076
HKD	0.73	0.36	0.84	0.98	6.66	1.29	0.26	4,073
INR	3.13	2.24	0.24	5.49	45.80	4.50	1.69	2,124
JPY	4.98	2.30	0.63	4.04	47.68	8.22	2.62	4,076
KRW	7.70	8.72	0.48	4.02	26.03	17.07	1.95	1,829
MYR	7.99	10.38	0.84	4.93	50.67	14.84	1.29	3,903
NZD	8.84	5.25	0.50	19.84	831.00	13.77	4.01	4,073
PHP	12.63	7.46	0.51	0.97	4.43	21.65	4.52	1,813
SGD	5.36	3.15	0.86	3.80	23.44	7.10	3.08	4,072
THB	11.70	9.57	0.43	6.08	57.83	16.48	5.19	1,834
TWD	9.35	9.39	0.68	1.33	3.15	27.36	2.57	1,825

Note: Panel a) of the table presents descriptive statistics for the daily exchange rate returns (daily change in log exchange rate) in percent per year, calculated as the daily change in log exchange rate times 100 and using 250 trading days per year. All exchange rates are expressed as using the US dollar (USD) as the base currency. Panel b) of the table presents descriptive statistics for the daily relative bid-ask spreads, the median of the intraday bid-ask spread divided by the mid-quote, expressed in basis points. Reported statistics for both panels are the mean (Mean), standard deviation (σ), first order autocorrelation ($\rho(1)$), skewness of the distribution (Skew.), kurtosis of the distribution (Kurt.), the 90th- and 10th- percentiles (p90 and p10) of the distribution, and the number of daily observations (Obs.)

provide each dealer in the interdealer market with a more centralized marketplace and more efficient matching. Two electronic brokers exist in today's foreign exchange market: Reuters Dealing 3000, a successor to the Reuters Dealing 2000-2 introduced in April 1992, and EBS (Electronic Broking Services). EBS was established in September 1993, and acquired the short-lived Minex platform launched by Japanese banks six months earlier. The market has settled on a fragmentation, where EBS dominates trading the US dollar against the euro, the Swiss franc and the Japanese yen, whereas Reuters dominates trading in the British pound, the currencies of other Commonwealth nations and minor currencies (Rime, 2003; Ito and Hashimoto, 2006).

A further implication of the arrival of electronic platforms for the interdealer market, as well as for customers, is increased cost-effectiveness and greater competition. Lower transaction costs are one of the drivers of increased turnover in the foreign exchange market over the last 20 years (King and Rime, 2010; King, Osler, and Rime, 2012).

In this paper, we use data on trading in the interbank market obtained from the Reuters trading platforms. Data for the most liquid currencies in our sample were obtained from the Reuters electronic broker, the Reuters Dealing 2000-2/3000 platform. Data for the smaller currencies in our sample, specifically the KRW, the MYR, the PHP, the THB and the TWD were obtained from the conversational ("chat") platform Reuters D2000-1, on which the majority of trades is carried out. The data obtained from the Reuters interdealer platforms provide, on a tick-by-tick basis, signed transactions, volumes and bid-ask spreads. For the following six currencies we have data back to January 8, 1996: the AUD, the HKD, the JPY, the NZD, the SGD, and the MYR. Observations for the INR start July 14, 2003, whereas observations for the KRW, the PHP, the THB, and the TWD start September 20, 2004. All series end October 5, 2011. Daily series are compiled by aggregating over 01:00 to 18:00 GMT, capturing the hours with the most trading activity as documented by King et al. (2012). The cumulative order flow for each exchange rate is shown in Figure 1. Over such a long time series the cumulative flows appear to be very smooth. In canonical microstructure models, it is unexpected order flow that moves asset prices (see e.g. Evans, 2011), and we will later use the difference of the cumulative flow together with lagged difference of flow as a proxy for the unexpected portion in our empirical implementation.

Table 2 panel b) presents descriptive statistics for relative bid-ask spreads for the eleven exchange rates. Relative bid-ask spreads are stated in basis points of the mid-quote. The bid-ask spreads are quite narrow over the entire sample. On average, a $1 million round-trip transaction in the JPY would cost $498. Furthermore, spreads have declined over the sample for all currencies exept the KRW and the MYR (see Figure 4 below). The same round-trip transaction in the JPY would only have cost about $250 at the beginning of October 2011, a roughly 50% reduction in transaction costs relative to the average over the 15-year sample period.

It appears from Table 2 panel b) that the cross-section pattern of relative bid-ask spreads is not exclusively one of liquidity, as given by each currencies' share of average total daily spot volume reported by the BIS. In particular, the spread in the USD/HKD exchange rate is by far the narrowest of the group, averaging only 0.73 basis points over the entire sample. Furthermore, its spread shows the lowest volatility among the eleven, with a standard deviation of 0.36 basis points, and a high persistence with a first order autocorrelation of 0.84. Low and predictable trading costs for the HKD are not surprising, given the stationarity of the exchange rate, a reflection of the HKD's strict currency board regime.

At the other end of the scale are the THB and the PHP. Both have double-digit roundtrip transaction costs as stated in basis points, and relatively high volatility and low persistence in their spreads. From Table 1 it is evident that these are the two smallest currencies in our sample in terms of the share of average total global spot volume. Although these currencies were fixed to some degree, panel a) of Table 2 shows that although controlled through managed floating arrangements, daily price movements on average have been substantial — in fact, the largest of the eleven currencies.

Between these extremes we find the major floating currencies: the AUD, the JPY, and the NZD. These currencies are the region's largest in terms of shares of total global spot volume, accounting for nearly 87% of the combined share of the region as a whole from Table 1. This degree of liquidity is reflected in the relative spreads in the interbank market shown in Table 2 panel b). The AUD/USD and USD/JPY exchange rates have relatively narrow and persistent spreads with low volatility. The relative spread in the NZD/USD exchange rate, however, is nearly twice that of the AUD and the JPY, averaging 8.84 basis points over the sample with lower persistence and much higher volatility. Furthermore, the distribution of the NZD/USD relative spreads is highly leptokurtic and positively skewed, indicating fat tails particularly at the high end of the distribution. These results seem plausible, given that the NZD is by far the least liquid of the major floating currencies in our sample.

Table 3 panel a) presents descriptive statistics for daily order flow in the eleven exchange rates. We do not have information on the volume of each trade. Order flow is therefore derived by matching the transaction price with the ask or bid price and creating a trade indicator that takes the value $+1$ (-1) if the initiator of trade bought (sold) the base currency. Daily order flow is the sum of the trade indicators from 01:00 to 18:00 GMT. Earlier studies (Killeen, Lyons, and Moore, 2006; Lyons and Moore, 2009) have shown that using volume-based rather than indicator-based order flow yields very similar results, probably because in the interbank market, trades are largely standardized at minimum volume of 1 million units of base currency. The first column of Table 3 panel a) shows that on average the AUD, the JPY, the NZD, the THB and the TWD experienced daily net USD selling-pressure, whereas the opposite holds for the remaining currencies.

When the average daily order flow is viewed in the context of the carry trade, the average daily buying-pressure on the AUD and the NZD make sense. In a carry trade an investor buys high interest rate currencies and sells low interest rate currencies. This is tantamount to betting that the uncovered interest rate parity (UIP) will not hold over the investment horizon, in other words, that movement in the exchange rate will wipe out the gain from the interest rate differential. Given the positive interest rate differentials of the AUD and the NZD relative to the USD over the sample, we would expect the flow in these crosses to result in net USD selling pressure. The fact that the JPY is a major funding currency for the carry trade, and given its negative interest rate differential relative to the USD over most of the sample, we would expect average flows to result in net buying -pressure on the USD in this cross. The lack of such a pattern for the JPY in our data warrants some careful consideration. Shift of trading in the JPY from Reuters onto the EBS platform may imply that our data from

Reuters is not sufficiently representative to capture such trends — an implication we will explore in detail in sections 3 and 4.

Daily order flows are quite volatile, as their standard deviations indicate. In particular, our two main currencies for the carry trade on the Reuters platform, the AUD and the NZD, are among the three currencies with highest volatility in daily order flow. The first order autocorrelation appears modest for most of the exchange rates, with the KRW and the PHP being possible exceptions. All distributions of daily order flow, apart from that of the KRW, are leptokurtic.

Table 3
Descriptive Statistics of FX Quantities

	Mean	σ	$\rho(1)$	Skew.	Kurt.	p90	p10	Obs.
a) Interbank order flow								
AUD	-16.36	271.50	0.11	0.44	7.80	278.00	-293.90	4 076
HKD	3.15	31.12	0.19	0.23	9.14	38.00	-26.10	4 074
INR	27.61	126.54	0.27	0.18	4.54	183.00	-116.00	2 124
JPY	-34.76	61.24	0.42	-0.11	5.17	30.00	-111.00	4 076
KRW	6.72	64.21	0.72	0.31	2.64	97.00	-72.00	1 829
MYR	0.77	7.18	0.19	0.80	20.72	7.00	-5.00	4 015
NZD	-7.17	103.56	0.12	0.47	11.76	82.00	-108.20	4 073
PHP	7.42	15.57	0.67	-0.01	4.09	27.00	-11.00	1 813
SGD	10.21	57.82	0.20	0.94	9.66	73.00	-45.00	4 072
THB	-5.24	17.43	0.22	2.33	33.26	11.00	-24.00	1 834
TWD	-20.30	21.85	0.54	0.02	4.11	4.00	-47.00	1 825
b) Volume (number of trades)								
AUD	5 394	5 221	0.89	1.64	6.26	13 093	707	4 076
HKD	402	306	0.88	1.25	4.25	863	125	4 074
INR	1 245	936	0.78	0.80	2.86	2 708	220	2 124
JPY	1 062	609	0.77	1.37	6.51	1 838	405	4 076
KRW	122	58	0.73	0.75	3.47	207	57	1 829
MYR	48	61	0.87	2.48	10.90	120	6	4 015
NZD	1 471	1 483	0.87	1.35	4.80	3 591	196	4 073
PHP	39	21	0.67	0.49	2.98	67	12	1 813
SGD	659	578	0.88	1.66	7.21	1 422	102	4 072
THB	109	65	0.72	1.64	8.05	194	46	1 834
TWD	92	31	0.42	-0.12	4.45	130	59	1 825

Note: Panel a) of the table contain descriptive statistics for interbank order flow on the Reuters platforms. Order flow is the daily sum of buyer initiated trades (on the ask-quote) minus the sum of seller initiated trades (on the bid-quote) between 01:00 and 18:00 GMT. Panel b) of the table contain descriptive statistics for the daily total number of trades. All exchange rates are stated using the US dollar (USD) as the base currency. Reported statistics for both panels are the mean (Mean), standard deviation (σ), first order autocorrelation ($\rho(1)$), skewness of the distribution (Skew.), kurtosis of the distribution (Kurt.), the 90th- and 10th-percentiles (p90 and p10) of the distribution, and the number of daily observations (Obs.)

Table 3 panel b) presents descriptive statistics for the daily volume of trading in the currency pairs in the sample, given by the total number of daily trades in the base currency of each exchange rate. Two of the major floating currencies of the region, the AUD and the NZD, stand out with large volumes of trading relative to the others. The daily average of trades in the USD/JPY exchange rate is illustrative of the shift of trading in the JPY onto the EBS platform. Table 1 shows that the JPY's share of global average daily turnover has remained fairly constant since 1995, while total global average turnover has increased more than threefold. The average daily trading volume in the JPY should dwarf the volumes of the two Australasian currencies in our sample, given its global importance. Figure 2 plots the volumes over time. Figure 2d shows that daily trading volume in the JPY has all but evaporated over the last 15 years on the Reuters platform, consistent with the shift onto the EBS platform. Two implications of trading data in the JPY are thus important for our subsequent analysis: First, although trading on the Reuters and EBS platforms might be correlated, if all informative trading in this cross is on the EBS platform, our results would be expected to suffer and have low explanatory power and statistical significance of order flow; second, results for the JPY should be stronger in the early years of our sample (when trading activity in the JPY on the Reuters platform were larger) than in later years. We include the JPY in our subsequent analysis to shed light on this hypothesis, but the paucity of data regarding the JPY should be borne in mind when drawing conclusions.

The lack of trading in the PHP on the Reuters platform is also a concern regarding our data. The special structure of the Philippine interbank market is reflected in the high relative bid-ask spread in panel b) Table (2) and the low volume of trading in panel b) Table (3). In the Philippines, commercial banks that are members of the Bankers Association of the Philippines and the central bank trade foreign exchange through the Philippine Dealing System (PDS).[12] As for the JPY, Reuters interdealer data might suffer from such a lack of trading activity, possibly limiting the informational content of flows. Results for the PHP in our subsequent analysis, though interpreted with care, are expected to reflect this paucity of data and have low economic and statistical significance and low explanatory power.

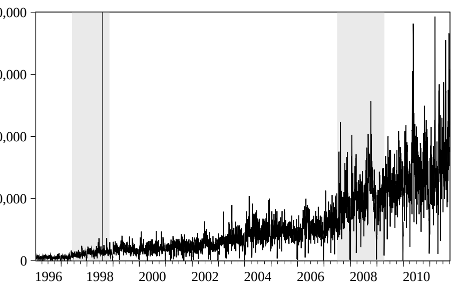
Another feature of Figure 2 is the steep increase in volume in nearly all exchange rates over the past decade, which accords with the 2010 triennial report from BIS. Apart from the JPY and the TWD, all currency pairs exhibit this pattern of higher daily trading volume. The trading volumes in the USD/MYR exchange rate shown in Figure 2f are a result of the successful peg maintained by the Malaysian authorities. Trading volumes plummeted in the latter stages of the Asian and Russian financial crises, and remained at very low levels until the peg was relaxed over the summer of 2005. The New Taiwan dollar is another interesting case, evincing a nearly stable volume over the entire sample. Table 3 panel b), also show that daily volatility in the volume of trading in the TWD is low compared with most other currencies. In addition, the volume of TWD trading is the least autocorrelated, and the TWD is the only currency whose distribution shows a (slight) negative skewness.

3 Long-Run Results

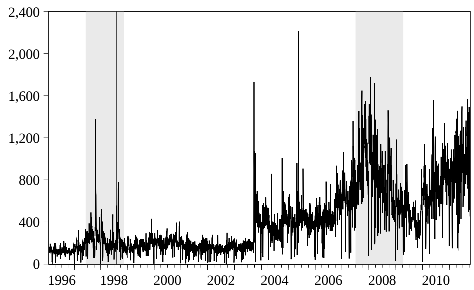
In the portfolio shifts model of Evans and Lyons (2002b), order flow conveys information that FX markets need to aggregate. Hence, order flow is a proximate determinant

[12] A thorough description of the Philippine interbank market is given in the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions*.

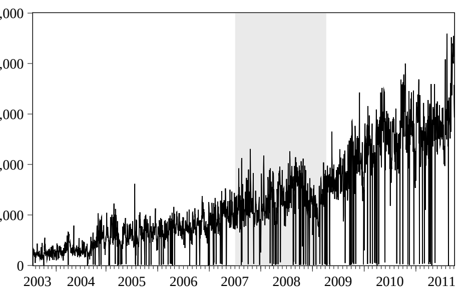
Figure 2
Daily Trading Volume (Number of Trades)



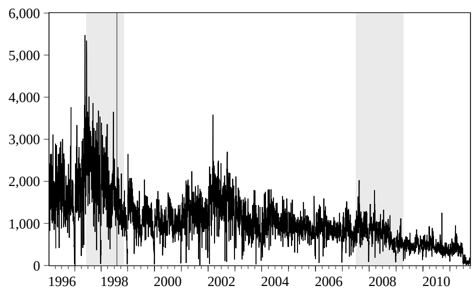
(a) Australian dollar (AUD)



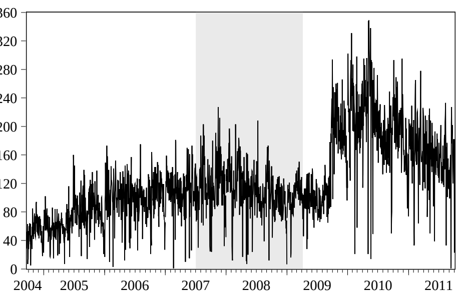
(b) Hong Kong dollar (HKD)



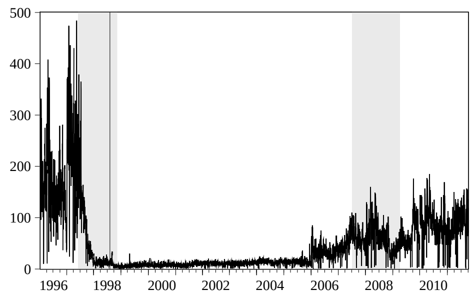
(c) Indian rupee (INR)



(d) Japanese yen (JPY)



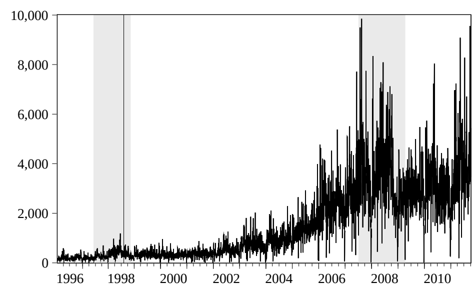
(e) Korean won (KRW)



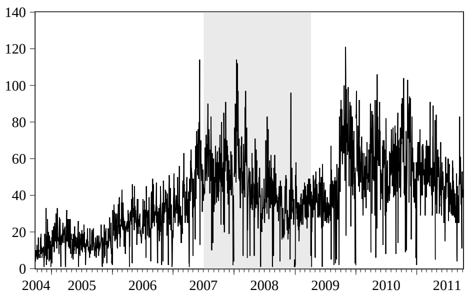
(f) Malaysian ringgit (MYR)

Note: The graphs show the total number of daily trades in the base currency of each exchange rate. All exchange rates are quoted using the US dollar (USD) as the base currency. Shading indicates the 1997–98 Asian Financial Crisis (defined as occurring between 6/01/1997 – 7/31/1998), the 1998 Russian Financial Crisis (between 8/1/1998 – 10/31/1998) and the 2007–09 Global Financial Crisis (between 7/01/2007 – 3/31/2009).

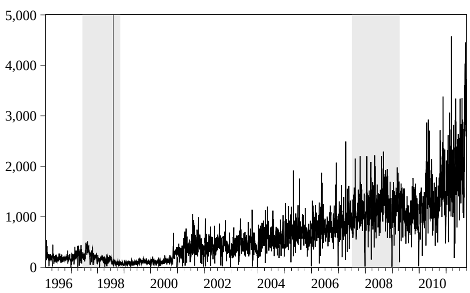
Figure 2
Daily Trading Volume (Number of Trades) (Continued)



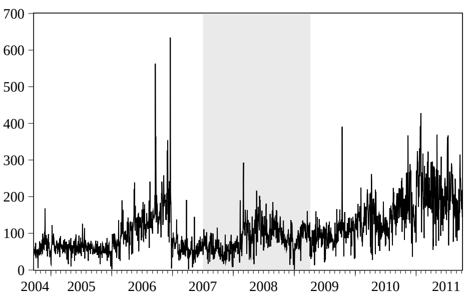
(g) New Zealand dollar (NZD)



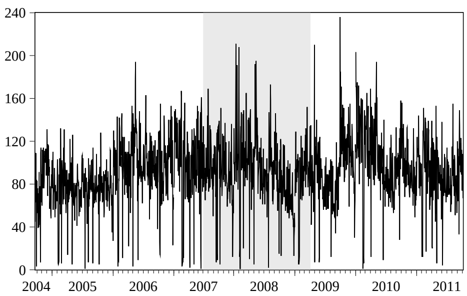
(h) Philippine peso (PHP)



(i) Singapore dollar (SGD)



(j) Thai baht (THB)



(k) New Taiwan dollar (TWD)

Note: See previous graph for details.

of exchange rates. In particular, net purchasing pressure on the USD (positive order flow) should increase the price of the USD. We estimate the impact of order flow on each individual currency as

$$\Delta s_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \lambda \Delta s_{t-1} + \varepsilon_t, \tag{1}$$

where Δs_t is the change in the log of the closing mid-quote exchange rate, using the USD as base currency, between day $t-1$ and t multiplied by 100, and x_t is order flow over day t standardized by its standard deviation. The specification further controls for price movements and order flow from the previous trading day, Δs_{t-1} and x_{t-1}, respectively. The first control captures feedback-trading (though autocorrelation for most currencies were found in Table 2 to be modest), while the second control is a simple way to account for predictable order flow which cannot represent the non-public information order flow impact supposedly captures. The approach taken here is closely related to that of Chordia et al. (2002) and Chordia and Subrahmanyam (2004) for US equity markets.

Results from the estimation of equation (1) for each currency are presented in the first row (I) in Table 4. Estimates of the contemporaneous effect of order flow on exchange rates, β_0, are given in the column *OF*. Estimated coefficients of the effect of lagged returns and order flow, λ and β_1 are not reported in order to save space. Furthermore, the adjusted R^2s reported are those of a separate regression using only contemporaneous order flow, excluding controls. This approach has been chosen to illustrate the explanatory power of the contemporaneous order flow alone. Two main conclusions can be drawn from the estimation of equation (1): First, order flow is correctly signed and is an economically significant determinant of the exchange rates of all currencies except the KRW. The positive sign on order flow implies that increase in net buyer initiated trades (trades on ask) increased the price of the USD measured in the FCU. Second, order flow is statistically significant (measured by high t-values) for all exchange rates but the USD/PHP.

The economic effect of order flow can be illustrated by the AUD.[13] As row (I) of Table 4 shows, a one standard deviation increase in net USD purchasing pressure on average appreciates the USD 0.47% relative to the AUD, or about 55% of the standard deviation in daily returns. As a comparison, Evans and Lyons (2002b) found that a $1 billion net purchasing pressure appreciated the USD on average 0.54% relative to the Deutsche mark. Assuming that as a lower bound the average trade in the AUD/USD is at Reuters platform minimum of $1 million, a one standard deviation increase in order flow amounts to about $272 million in our sample. The effect of order flow is thus somewhat stronger in our data, but one have to be aware that this is a lower limit (making the difference less clear) and that the lower liquidity of the AUD compared to the Deutsche mark probably also contributes to a higher price impact. Similar economic significance in relation to the standard deviation of annualized daily returns is found for most of the other exchange rates, excluding the incorrectly signed coefficient for the KRW and the statistically insignificant coefficient for the PHP: HKD 41%; INR 47%; JPY 26%; MYR 10%; NZD 49%; SGD 36%; THB 20%; TWD 29%.

[13] Economic effect of order flow is here the order flow coefficient times order flow standard deviation relative to exchange rate volatility.

Table 4
The Long-Run Effect of Order Flow

		OF	Int.rate	Slope	Equity	Vol.	R^2	Obs.
AUD	I	0.4655					0.29	4074
		(25.67)						
	II	0.4474	-0.6622	-0.5163	0.0466	0.5379	0.34	4068
		(26.85)	(-2.03)	(-2.82)	(4.13)	(3.89)		
HKD	I	0.0132					0.15	4072
		(11.82)						
	II	0.0132	-0.0087	-0.0009	0.0000	0.0011	0.17	4066
		(11.76)	(-3.01)	(-0.38)	(-0.01)	(0.42)		
INR	I	0.2034					0.20	2122
		(15.84)						
	II	0.1894	-0.0132	0.0154	-0.0135	0.1971	0.25	2116
		(14.25)	(-0.12)	(0.14)	(-2.99)	(4.22)		
JPY	I	0.1833					0.05	4074
		(9.01)						
	II	0.1701	-2.1715	-2.4105	-0.0306	-0.5622	0.18	4068
		(8.96)	(-8.50)	(-10.05)	(-4.87)	(-9.21)		
KRW	I	-0.2459					0.01	1827
		(-6.98)						
	II	-0.2047	0.6384	0.6568	-0.0695	0.5081	0.19	1821
		(-6.23)	(1.88)	(2.25)	(-4.35)	(5.58)		
MYR	I	0.0547					0.01	4013
		(7.42)						
	II	0.0518	0.2089	0.2000	-0.0253	0.1642	0.04	4009
		(7.48)	(1.34)	(1.21)	(-4.50)	(4.34)		

Note: The table presents results from the estimation of the Evans and Lyons (2002b) portfolio shifts model for each exchange rate, using the USD as the base currency, over the Reuters interdealer sample at a daily frequency. All specifications are estimated using Ordinary Least Squares with Newey-West Heteroscedastic and Autocorrelation Consistent standard errors. The reported numbers are coefficient-values from two different regression-formulations, with t-values given in parenthesis below. The number of daily observations for each currency pair is given in the last column (Obs.). Row (I) column *OF*, gives the coefficient estimate of β_0 for each exchange rate from the regression

$$\Delta s_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \lambda \Delta s_{t-1} + \varepsilon_t,$$

where Δs_t is the change in the log of the closing mid-quote exchange rate between day $t-1$ and t multiplied by 100, and x_t is order flow over day t standardized by its standard deviation. The adjusted R^2 in row (I) is from a separate regression with only contemporaneous order flow (no lags). Row (II) includes the change in the 3-month interest rate differential between the country in question and the U.S. (Int.rate), the change in the difference of the slope of the yield curve calculated as a two year government bond less the 3-month interest rate between the country in question and the U.S. (Slope), the change in the equity index return differential between the country in question and the U.S. (Equity), and the change in the 3-month implied volatility of the J.P. Morgan VXY index (Vol.).

Table 4
The Long-Run Effect of Order Flow (Continued)

		OF	Int.rate	Slope	Equity	Vol.	R^2	Obs.
NZD	I	0.4131					0.24	4071
		(19.13)						
	II	0.3968	-0.2968	-0.3058	0.0588	0.3991	0.28	4065
		(20.64)	(-1.51)	(-1.87)	(6.14)	(4.86)		
PHP	I	0.0146					0.00	1811
		(0.83)						
	II	0.0012	0.2300	0.1871	-0.0163	0.1860	0.06	1805
		(0.07)	(2.73)	(2.30)	(-3.93)	(4.40)		
SGD	I	0.1379					0.13	4070
		(16.50)						
	II	0.1382	0.2239	0.1638	-0.0013	0.0430	0.15	3564
		(16.99)	(1.70)	(1.28)	(-0.36)	(1.32)		
THB	I	0.1254					0.04	1832
		(8.27)						
	II	0.1242	0.1674	0.1573	0.0027	0.0721	0.10	1826
		(8.34)	(1.34)	(1.38)	(0.43)	(1.36)		
TWD	I	0.0903					0.05	1823
		(8.66)						
	II	0.0810	0.1099	0.1467	-0.0124	0.0672	0.09	1817
		(7.71)	(0.96)	(1.33)	(-4.39)	(2.58)		

Note: See previous Table for details.

As a second specification, some proxies for public information that might influence the price determination of exchange rates are included, and as such is closer to the portfolio shifts model of Evans and Lyons (2002b). Macroeconomic information at a daily frequency is scarce. In order to check for the robustness of the order flow impact, we choose to incorporate a rather broad set of publicly available variables given the frequency: the three-month interest rate differential; the difference of the slope of the yield curve, calculated as a two year government bond less the three-month interest rate between the country in question and the U.S.; the equity index return differential between the country in question and the U.S.; and the J.P. Morgan VXY volatility index.[14] All variables are in first-differences in order to avoid problems of non-stationarity. The second specification thus amounts to

$$\begin{aligned}\Delta s_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \lambda \Delta s_{t-1} \\ + \phi_i \Delta\left(i^{FCU}_{t,3m} - i^{USD}_{t,3m}\right) + \phi_s \Delta\left[\left(i^{FCU}_{t,2y} - i^{FCU}_{t,3m}\right) - \left(i^{USD}_{t,2y} - i^{USD}_{t,3m}\right)\right] \\ + \phi_e \Delta\left(r^{FCU}_t - r^{USD}_t\right) + \phi_v \Delta\left(vxy_t\right) + \varepsilon_t, \quad (2)\end{aligned}$$

where the first part is equivalent to equation (1) and the rest of the variables are defined above.

The motivation for the use of interest rate differentials needs no further justification. The yield curve slope is included to capture inflation expectations. The inclusion of equity return differentials is motivated by Hau and Rey (2006). Hau and Rey develop a model in which exchange rates, equity returns and portfolio equity flows are jointly endogenously determined. In their model, higher equity returns in a given currency are associated with a depreciation of the currency, which amounts to an "uncovered equity parity". Our specific motivation for including the J.P. Morgan VXY volatility index is based on the recent contribution by Menkhoff, Schmeling, Sarno, and Schrimpf (2011), who show empirically that global FX volatility influence the returns to individual currencies.[15]

The results from the estimation of equation (2) are presented in the second row (II) for each currency in Table 4. As above, the estimates of the contemporaneous effect of order flow, β_0, are given in the column *OF*, while the effects of lagged returns and order flow, λ and β_1, are not stated. The coefficient estimates on the public information variables are reported in the columns *Int.rate*, *Slope*, *Equity* and *Vol.* (for volatility).

Adding a whole set of publicly available information in the second row for each currency in Table 4 does little to change our results for the order flow impact. The explanatory power of the second specification is somewhat greater than that of order flow alone, but the coefficient estimates of order flow and their statistical significance are stable.

For relatively large currencies such as the AUD, the HKD, the INR, the NZD and the SGD, explanatory power is high compared to what is usually found when

[14] All of the interest rates and the J.P. Morgan VXY index are obtained from Thomson Reuters EcoWin. Daily equity returns are computed using the FTSE country-specific equity indices provided by Thomson Reuters Datastream.

[15] The J.P. Morgan VXY index is a volatility index based on implied volatilities from currency options of G7 countries, and should thus serve as a reliable proxy for global FX volatility.

conditioning on public information variables alone, and almost all of the explanatory power comes from order flow. This confirms earlier results like that of Evans and Lyons (2002b). However, for some currencies the increase in explanatory power when adding public information variables is substantial. The adjusted R^2 of, e.g., the JPY and the KRW, increases from 5% to 25% and from 1% to 31%, respectively. The low explanatory power of contemporaneous order flow for the JPY stands out amongst the major currencies. However, given the paucity of our data with regard to the JPY discussed in section 2.2, this is no surprise. The hypothesis that virtually all informative trading in the JPY is now on the EBS platform appears to be plausible.

The results for the KRW and the PHP require some special attention. We believe the negative estimate of contemporaneous order flow on the KRW to be best explained in the light of the crises in our sample, and defer a special treatment of the KRW to section 4. Given the paucity of our data regarding the PHP discussed in section 2.2, the lack of significance and explanatory power is not surprising given that a majority of interbank trading in PHP is on the PDS and not on Reuters. In addition, the PHP is the least traded currency in our sample, accounting for only 0.15% of average daily spot FX volume (BIS, 2010).

Interestingly, the results on the impact of order flow do not fit into a cross-sectional taxonomy of either liquidity or exchange rate regimes. For instance, Table 1 shows that the AUD is the second most traded currency in our sample and has the largest economic effect of order flow. The INR is the seventh most traded currency in our sample according to the BIS, and yet has the third largest economic effect of order flow. Results are also somewhat surprising with regard to exchange rate regimes. Killeen et al. (2006) develop a model linking the effect of order flow to exchange rate regimes where portfolio shifts affect exchange rates *more* under a flexible regime. The intuition is that return volatility shrinks to zero under perfectly credible exchange rates, causing rational investors to be more willing to absorb portfolio shifts without fear of asymmetric information than in more flexible and volatile exchange rates. In our sample, the HKD is the most rigid currency, yet has the fourth largest economic effect of order flow. Indeed, the small movements of the USD/HKD exchange rate allowed within the currency board regime are in large part explained by order flow, while we would expect order flow not to be a determinant for a credibly fixed currency like the HKD. Of course, one could argue that the effect is due to the dividing by a small number (HKD-return standard deviation), but this does not explain why the coefficient is significantly different from zero.

As for the public information variables, the results are to a large extent as expected given earlier problems of finding clear effects from macroeconomic variables. The notable exception is the effect of FX volatility. In the case of increased uncertainty in the FX market, one would expect to see 'a flight to safety'. This would amount to a depreciation of the currencies in our sample relative to the USD, as investors move into the USD. Apart from the JPY, the effect of volatility is correctly signed for all currencies, and statistically significant for seven out of the eleven. The case of the JPY is somewhat special, given the yen's dominance as a funding currency for the carry trade. In the event of market turbulence, the yen is often found to appreciate because of its 'safe-haven' status and the unwinding of carry trade positions. The effect for the yen is furthermore strongest of all the currencies. Our results are similar to those found by Menkhoff et al. (2011).

The results as presented in Table 4 are strong for the six currencies constituting our longest sample; the AUD, the HKD, the JPY, the NZD, the MYR and the SGD. This motivates a more thorough analysis of the effect of order flow in the region as a whole using these six currencies. Due to the wide range of currency regimes in Asia, the problems associated with *de jure* exchange rate classification, and the varying degrees of liquidity in our currencies, we would expect a high degree of noise in the effect of order flow for individual currencies —at least for the least liquid ones. Several contributions to the literature have studied the effect of order flow in one currency pair on the return in another pair (see Evans and Lyons, 2002a; Lyons and Moore, 2009; Daníelsson, Luo, and Payne, 2011). Two papers in particular are close to our hypothesis of a regional order flow effect. Evans and Lyons (2002a) develop a model in which a link between information in one currency pair and return in another arises because of dispersed information coupled with the portfolio problem of allocating wealth across all currencies. Evans and Lyons further document empirically that the order flow in the German mark and Swiss franc against the USD have substantial impact on returns in a four month long sample of other less liquid European currencies. Daníelsson et al. (2011) document cross-market order flow effects in the major exchange rates: EUR/USD, EUR/GBP, GBP/USD and USD/JPY. Daníelsson et al. attribute this to the possibility of information on a single currency being exploited at the lowest cost in the most liquid exchange rate. Liquidity providers in the less liquid exchange rates involving the same currency will, however, be cognizant of this incentive and adjust quotes accordingly.

Our contribution to the literature on cross-market order flow effects is that of using principal components. In line with conclusions by Evans and Lyons (2002a) and Daníelsson et al. (2011), a common regional flow may possibly be of greater importance for the currency movements of individual countries in the Asia-Pacific region than individual flows. Table 5 presents the results from SUR (Seemingly Unrelated Regressions) systems with three different specifications. The first SUR system is specified with individual returns in all the eleven exchange rates estimated on the principal component of the flows of the six currencies with the longest sample: the AUD, the HKD, the JPY, the NZD, the MYR and the SGD. The second specification is the same as the first, except that the principal component of the flows of the three major floating currencies of the region, the AUD, the JPY and the NZD, are used instead. Finally, the third SUR system uses all six individual flows from the first system as right-hand side variables.

The first column of Table 5 shows results from the first specification of the SUR system. Apart from the JPY, order flow is now correctly signed and highly statistically significant for all currencies. All exchange rates load positively on the common regional component. This also holds for the KRW and the PHP, the two troubling currencies from Table 4. In second column of Table 5, the HKD, the MYR and the SGD are excluded from the creation of the principal component flow, and only the region's major floating currencies are used. The sensitivity of the loadings of each currency, excluding the JPY, is minimal, an indication that a regional flow is highly dependent upon the information in the three major currencies of the region. The third column of Table 5 shows the loadings of the eleven exchange rates on each of the six individual flows used to construct the principal component in the first system, giving a similar picture of the regions' flows.

Table 5
SUR-type system

	PC (all)		PC (floaters)		Separate flows						
	Slope	R^2	Slope	R^2	AUD	HKD	JPY	MYR	NZD	SGD	R^2
AUD	0.351	0.30	0.364	0.29	0.3555	0.0350	0.0451	0.0142	0.1253	0.0909	0.32
	(25.09)		(24.76)		(16.93)	(2.65)	(3.85)	(1.48)	(4.71)	(6.28)	
HKD	0.004	0.02	0.002	0.01	0.0028	0.0124	0.0005	0.0009	-0.0005	0.0007	0.16
	(6.18)		(3.82)		(3.45)	(13.52)	(0.90)	(1.72)	(-0.72)	(1.06)	
INR	0.072	0.08	0.065	0.07	0.0633	0.0158	-0.0067	0.0577	0.0094	0.0445	0.10
	(11.02)		(9.75)		(5.35)	(1.82)	(-0.51)	(5.21)	(0.92)	(5.08)	
JPY	0.023	0.00	0.009	0.00	-0.0183	0.0054	0.1539	-0.0112	-0.0057	0.0829	0.06
	(1.71)		(0.69)		(-0.91)	(0.41)	(9.32)	(-1.13)	(-0.31)	(6.03)	
KRW	0.118	0.06	0.104	0.05	0.0574	0.0685	-0.0032	0.0799	0.0598	0.0715	0.07
	(10.02)		(8.49)		(2.32)	(3.51)	(-0.09)	(4.64)	(2.59)	(4.58)	
MYR	0.064	0.02	0.059	0.02	0.0440	0.0379	0.0285	0.0474	0.0246	0.0239	0.03
	(12.61)		(10.97)		(5.98)	(4.00)	(2.33)	(7.18)	(3.24)	(3.84)	
NZD	0.348	0.30	0.363	0.29	0.2134	0.0574	0.0454	0.0084	0.2650	0.0904	0.31
	(31.90)		(30.88)		(12.30)	(4.28)	(4.07)	(0.91)	(14.34)	(7.03)	
PHP	0.055	0.06	0.051	0.04	0.0448	0.0227	0.0243	0.0658	0.0118	0.0277	0.08
	(9.73)		(8.36)		(4.87)	(2.91)	(1.58)	(5.43)	(1.22)	(3.39)	
SGD	0.115	0.16	0.098	0.10	0.0711	0.0215	0.0423	0.0101	0.0300	0.1056	0.20
	(24.28)		(19.24)		(10.44)	(3.44)	(4.85)	(2.30)	(5.24)	(15.78)	
THB	0.043	0.02	0.039	0.01	0.0348	0.0026	-0.0002	0.0461	0.0075	0.0303	0.02
	(6.99)		(5.99)		(3.56)	(0.27)	(-0.01)	(3.63)	(0.72)	(3.57)	
TWD	0.051	0.09	0.044	0.07	0.0383	0.0248	-0.0167	0.0431	0.0116	0.0300	0.11
	(12.15)		(10.64)		(5.74)	(3.83)	(-1.51)	(5.56)	(1.92)	(5.40)	

Note: The Table presents the results from three different systems, where each equation has an exchange rate return using the USD as base currency as dependent variable and having the same right-hand side variables. The systems are estimated at daily frequency using using Ordinary Least Squares with Newey-West Heteroscedastic and Autocorrelation Consistent standard errors. In the first system the single regressor is the principal component based on the currency flows of the AUD, the HKD, the JPY, the MYR, the NZD, and the SGD. In the second system the principal component is based only on the flows of the major floating currencies of the region: the AUD, the JPY and the NZD. In the third system all flows of the first system are used as regressors. t-values are given in parentheses below the coefficient-values.

Summing up our long-run results for Asian and Australasian currencies, we find that order flow is an important determinant of exchange rates in the region. Both in economic and statistical terms, order flow is key to modeling the price change of Asian-Pacific currencies. Furthermore, we find a strong depreciatory effect of a region-wide outflow into the US dollar on all currencies in the region.

4 Turbulence

As noted above, a number of financial crises occurred around the world during the two decades since the early 1990s. In section 4.1 we begin our analysis of order flow in periods of market distress with a brief description of the crises we believe have been most important for the Asia-Pacific region within the range of our sample. Section 4.2 contains our empirical results regarding order flow and crises periods.

4.1 Turbulence in the Foreign Exchange Market

To illustrate periods of turbulence, we plot the Chicago Board Options Exchange (CBOE) VIX index and the J.PP Morgan G7 FX-volatility VXY index in Figure 3. The two volatility-indices, both based on implied volatilities, are complementary but also show that the crises of the early 2000s mentioned above did not have a particularly severe impact on the FX market. We will focus on three crises in our empirical analysis: the 1997–98 Asian financial crisis, the 1998 Russian (LTCM) crisis and the 2007–09 global financial crisis. The periods of these three crises are indicated in Figure 3 by shading.

During the 1997–98 Asian financial crisis (here defined as occurring between June 1, 1997, and the end of July 1998), uncertainty in global financial markets soared, as shown by the jump in the VIX index in Figure 3. The slight impact on the VXY FX-volatility index indicates that with respect to the FX market this was a regional crisis, and the major G7 currencies underlying the VXY did not experience a similar increase in volatility.[16] The Russian financial crisis (defined as occurring between August 1, 1998, and the end of October 1998), which required bail-out of Long-Term Capital Management (LTCM), had an even greater ripple effect on the global financial system than did the Asian financial crisis, as measured by the VIX index in Figure 3. The subsequent unwinding of the yen carry trade during the fall of 1998 led to a massive appreciation of the USD/JPY exchange rate and an increase in FX volatility.[17] During the 2007–09 global financial crisis (defined as occurring between July 1, 2007, and the end of March 2009), both the VIX and the VXY index can be seen to reach all-time highs after the collapse of Lehman Brothers, illustrating the severity of the crisis for financial markets.[18]

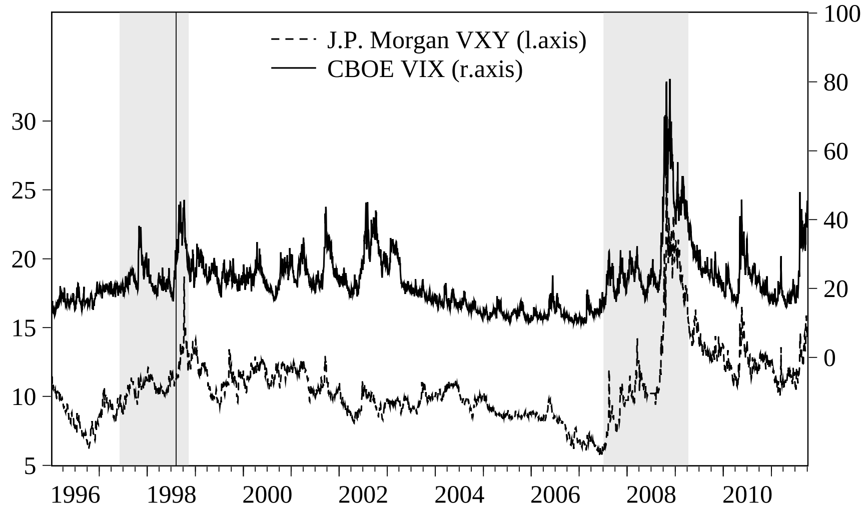
Two key features of FX markets during periods of distress, are increased trading volume and increased volatility of bid-ask spreads (Lyons, 2001; Melvin and Taylor,

[16]See Corsetti et al. (1999) for a thorough account of the build-up of the Asian financial crisis.

[17]See Kharas, Pinto, and Ulatov (2001) for an account of the Russian financial crisis.

[18]See Brunnermeier (2009) for an account of the early stages of the 2007–09 global financial crisis, Rose and Spiegel (2010) for cross-country causes and consequences, and Melvin and Taylor (2009) for an excellent account of the specific implications for the foreign exchange market.

Figure 3
Crises and Market Distress



Note: The figure shows the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), and the J.P. Morgan G7 Volatility Index (VXY), plotted from January 8, 1996 – October 5, 2011. Shading indicates the 1997–98 Asian Financial Crisis (defined as occurring between 6/01/1997 – 7/31/1998), the 1998 Russian Financial Crisis (between 8/1/1998 – 10/31/1998) and the 2007–09 Global Financial Crisis (between 7/01/2007 – 3/31/2009).

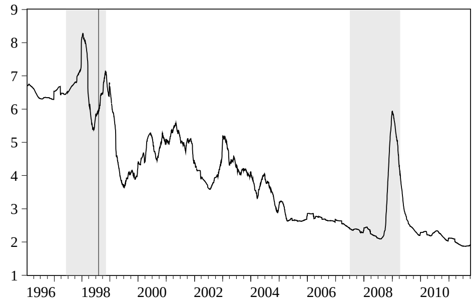
2009). Figure 2 shows increased trading volume in all currencies in our sample during the crises. This is not an indication of greater liquidity, but rather evidence of the "hot potato trading" (see Lyons, 2001) and reluctance to take on inventory (see Melvin and Taylor, 2009). Also, quite naturally, heterogeneous interpretation of rapidly moving public information will lead to high volumes in turbulent times.

Relative spreads for the eleven exchange rates over our sample are given in Figure 4. As in the findings of Melvin and Taylor (2009), volatilities of bid-ask spreads in our sample are highly influenced by market distress. Figure 4 shows pronounced spikes during the crises for all currencies but the HKD. Furthermore, large fluctuations in spreads occur for all currencies over the sample. The fact that the relative bid-ask spread for the USD/HKD exchange rate does not appear to be influenced by market distress in the same manner as the other exchange rates, is not surprising given the HKD's strict currency board regime.

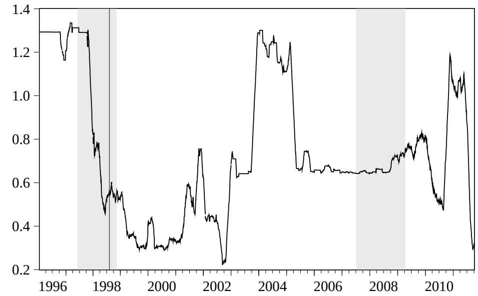
4.2 Order Flow and Turbulence

The implications for the FX market of the crises discussed above prompt the question of whether or not order flow is stable through periods of distress. Figure 5 presents rolling coefficient estimates of the effect of contemporaneous order flow on exchange rate returns, β_0, from the model in equation (1). The model is estimated using a rolling sample length of 250 observations (roughly one trading-year), re-estimated for every observation. The series of rolling coefficient estimates are plotted using the last date of each rolling sample. Thus, each plotted estimate in Figure 5 is the estimate over the preceding (trading) year. The grey band surrounding each series of coefficient

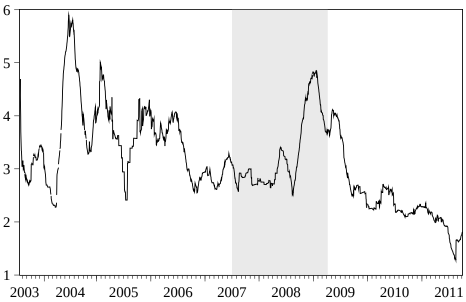
Figure 4
Relative Bid-Ask Spreads



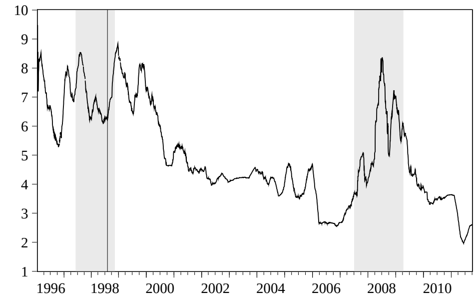
(a) Australian dollar (AUD)



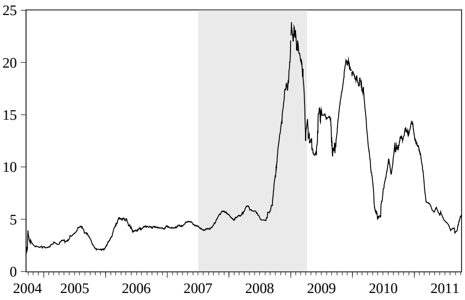
(b) Hong Kong dollar (HKD)



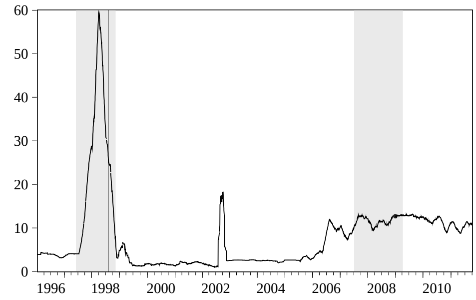
(c) Indian rupee (INR)



(d) Japanese yen (JPY)



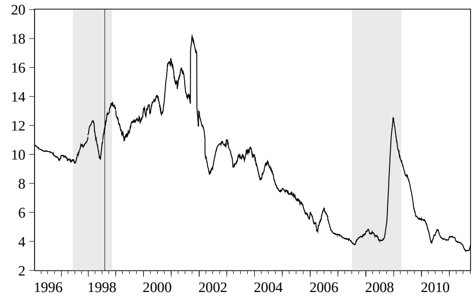
(e) Korean won (KRW)



(f) Malaysian ringgit (MYR)

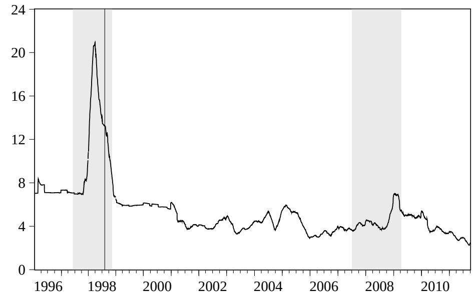
Note: Graphs show the 60-day moving average of relative spreads (bid-ask spread divided by the mid-point exchange rate) measured in basis points. All exchange rates, except the Australian dollar (AUD) and the New Zealand dollar (NZD), use the US dollar (USD) as base currency. Shading indicates the 1997–98 Asian Financial Crisis (defined as occurring between 6/01/1997 – 7/31/1998), the 1998 Russian Financial Crisis (between 8/1/1998 – 10/31/1998) and the 2007–09 Global Financial Crisis (between 7/01/2007 – 3/31/2009).

Figure 4
Relative Bid-Ask Spreads (Continued)

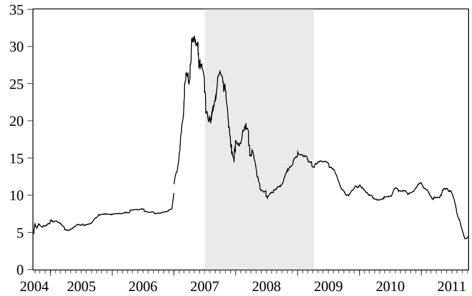


(g) New Zealand dollar (NZD)

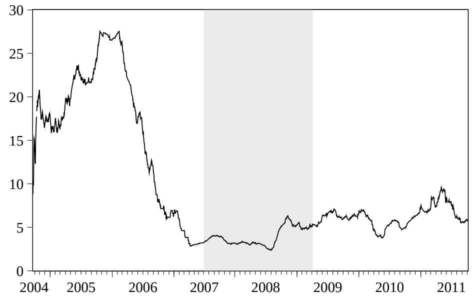
(h) Philippine peso (PHP)



(i) Singapore dollar (SGD)



(j) Thai baht (THB)



(k) New Taiwan dollar (TWD)

Note: See previous graph for details.

estimates is the 95% confidence interval.

Figure 5 clearly shows that the impact of order flow is even greater during times of distress in the FX market. During the 1997–98 Asian financial crisis and its Russian sequel, the coefficient estimates of order flow increases — for all currencies with a sample spanning these two crises. Pronounced peaks in economic and statistical significance appear in Figure 5. Coefficient estimates and statistical significance during the 2007–09 global financial crisis provide a similar picture.

We check for time-varying effects by interacting order flow with time-dummies, thereby obtaining the *excess effect* of order flow during crises. Table 6 presents results from the estimation of equation (2) using a dummy variable for each of the three crises in our sample; the 1997–98 Asian financial crisis (dAsia), the 1998 Russian financial crisis (dRus) and the 2007–09 global financial crisis (dGFC). We also include a dummy variable indicating the current sovereign debt crisis (dSDC). Since the current crisis is still ongoing at the time of writing, this dummy simply takes on the value 1 from beginning of May 2010 when a dramatic escalation of the Greek sovereign debt crisis triggered huge volatility in financial markets. The effects of publicly available information from equation (2) and return and order flow from the previous trading day have been omitted from the table for clarity of presentation.

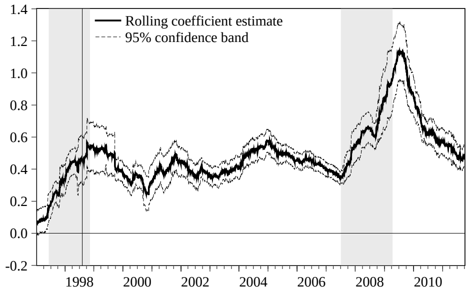
On the basis of the results in Table 6, two main conclusions can be drawn. First, the effect of order flow for exchange rate determination is not a result mainly driven by turbulence in the FX market. Second, the effect of order flow is time-varying and particularly strong during periods of market distress.

The coefficient estimates of order flow in the column *OF* of Table 6 is the effect of order flow on daily exchange rate return *net* of the crises in our sample. A comparison of these estimates with those of row (II) of Table 4 reveals strikingly small differences. The effect of order flow is thus omnipresent in the foreign exchange market, and not dominated by a few volatile sub-periods. The exception to this consistency is the coefficient for the JPY. The JPY order flow estimate and its statistical significance excluding all crises falls more than for the other currencies in our sample. This finding is in line with the hypotheses laid out in section 2.2. Although the interpretation of the JPY estimates requires some caution, the declining importance of the Reuters platform for the USD/JPY exchange rate is apparent in the data. The dividing-up of the effect of order flow over time impacts the JPY hard in that its trading volume on the Reuters platform peaked during the Asian/Russian financial crises, as seen in Figure 2d. Furthermore, in our data, the effect of order flow for the JPY monotonically declines from the Russian financial crisis onwards. This is a result of the decline of importance of the Reuters interdealer platform from the beginning of our sample to the end.

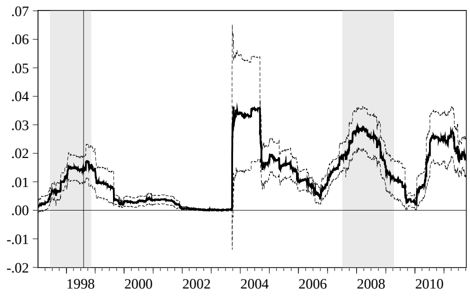
The results in Table 6 clearly indicate a time-varying effect of order flow. The region's major floaters — the JPY, the AUD, and the NZD — all show a significant increase in the importance of order flow during the crises (though one must bear in mind the special considerations regarding the JPY). Coefficient estimates indicate that during the Russian financial crisis, for example, the impact of a one standard deviation increase in net USD buyer-initiated trades increased the daily return on the AUD by an additional 1.7% — a strong effect.

Considering the HKD, the MYR and the SGD in addition to the regions' major floaters, reveals that the same time-varying pattern is evident for all six currencies

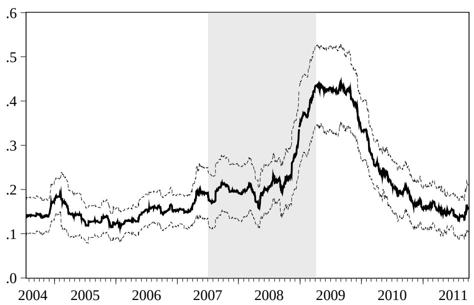
Figure 5
Rolling Order Flow-coefficients



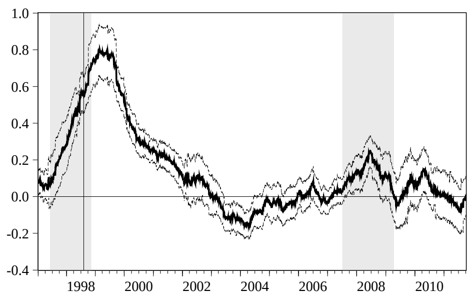
(a) Australian dollar (AUD)



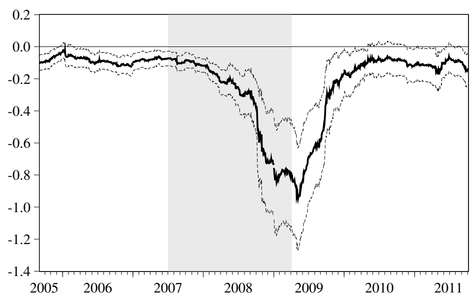
(b) Hong Kong dollar (HKD)



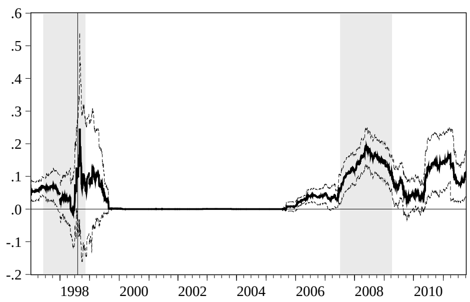
(c) Indian rupee (INR)



(d) Japanese yen (JPY)



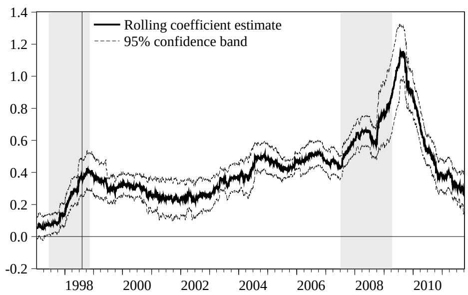
(e) Korean won (KRW)



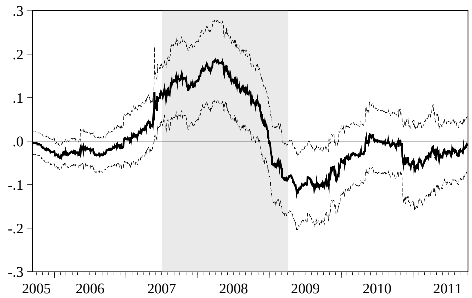
(f) Malaysian ringgit (MYR)

Note: The figure presents rolling coefficient estimates of contemporaneous order flow for each currency (β_0) from equation (1). The model is estimated for a rolling sample size of 250 observations, re-estimated for each observation. The model is estimated by OLS using Newey-West standard errors, with the dashed lines indicating the 95% confidence bands for the coefficient using robust standard errors. Shading indicates the 1997–98 Asian Financial Crisis (defined as occurring between 6/01/1997 – 7/31/1998), the 1998 Russian Financial Crisis (between 8/1/1998 – 10/31/1998) and the 2007–09 Global Financial Crisis (between 7/01/2007 – 3/31/2009).

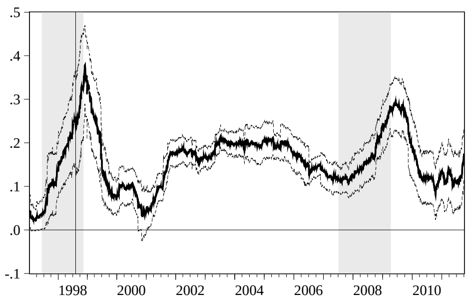
Figure 5
Rolling Order Flow-coefficients (Continued)



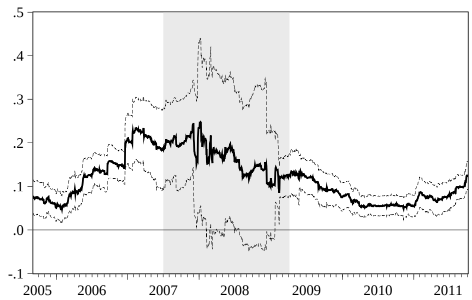
(g) New Zealand dollar (NZD)



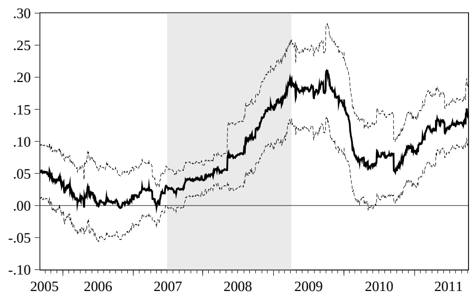
(h) Philippine peso (PHP)



(i) Singapore dollar (SGD)



(j) Thai baht (THB)



(k) New Taiwan dollar (TWD)

Note: See previous graph for details.

Table 6
The Time-Varying Effect of Order Flow

	OF	dAsia	dRus	dGFC	dSDC	R^2	Obs.
AUD	0.4853	1.0713	1.7153	0.4725	0.3041	0.34	4068
	(22.81)	(5.09)	(5.84)	(12.33)	(12.21)		
HKD	0.0135	0.0142	0.0133	0.0129	0.0129	0.17	4066
	(7.05)	(6.08)	(2.44)	(6.42)	(6.48)		
INR	0.1829			0.2606	0.1102	0.28	2116
	(13.31)			(8.30)	(5.97)		
JPY	0.0967	0.3160	0.6352	0.1309	0.1057	0.26	4068
	(5.51)	(9.19)	(4.60)	(2.92)	(1.26)		
KRW	-0.1326			-0.2288	-0.1244	0.31	1821
	(-4.94)			(-4.14)	(-3.33)		
MYR	0.0282	0.0567	0.6517	0.1211	0.0836	0.10	4009
	(5.68)	(1.43)	(1.43)	(5.50)	(3.40)		
NZD	0.4436	1.0739	1.1154	0.3742	0.3010	0.26	4065
	(16.33)	(6.52)	(3.49)	(10.95)	(7.47)		
PHP	0.0012			0.0474	-0.0307	0.08	1805
	(0.06)			(1.99)	(-1.34)		
SGD	0.1528	2.3887	1.9999	0.1385	0.0951	0.21	3564
	(13.99)	(7.15)	(3.53)	(8.62)	(5.68)		
THB	0.1354			0.1387	0.0916	0.10	1826
	(7.20)			(2.99)	(7.80)		
TWD	0.0623			0.0889	0.0865	0.11	1817
	(4.88)			(6.80)	(6.15)		

Note: The table presents results from a regression similar to equation (2), with the difference that order flow is allowed separate effects during each crisis by using interaction with dummy-variables. dAsia measures the effect of order flow during the Asian crisis, dRus measures the effect during the Russian crisis, dGFC the global financial crisis, and dSDC the sovereign debt crisis. All coefficients on the public information variables and lagged order flow and return are suppressed to save space.

constituting our longest sample. Order flow is even more important for price determination in the FX market during crises. All coefficient estimates are economically and statistically significant, apart from the effect during the 1997–98 Asian and Russian financial crises for the MYR. This is no surprise, when one looks at Figure 2f, and is directly attributable to the successful pegging of the ringgit by the Malaysian authorities during the later stages of the Asian/Russian crises. This finding for the MYR as return volatility approaches zero is consistent with Killeen et al. (2006).

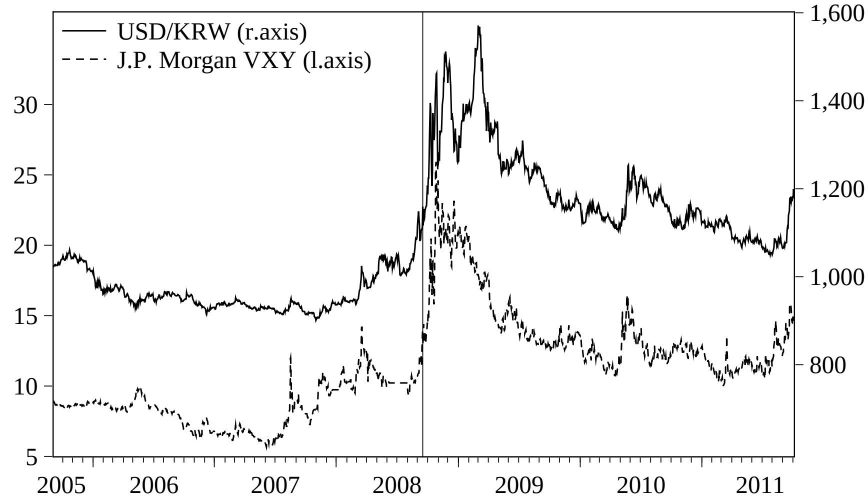
Finally, a look at the five currencies in our sample with shorter sample length; the INR, the KRW, the PHP, the THB and the TWD upholds our results to a large degree. There is a strong time-varying effect of order flow. The insignificant effect of order flow in the USD/PHP exchange rate in all periods but the global financial crisis, is possibly due to the special structure of interbank trading in the PHP.

The KRW stands out throughout our analysis. The effect of order flow is persistently found to be negative *and* significant, i.e. net USD purchases are found to *appreciate* the won relative to the dollar. In our view, a plausible explanation for this puzzle for the won is noisy data on order flow and market intervention. First, the informational content of order flow in the USD/KRW exchange rate appears to be somewhat limited, as indicated by both the limited explanatory power of order flow alone in Tables 4 and 6, and the significant loading of daily returns on the principal components over the entire 15-year-long sample in Table 5. Second, the consistently negative effect of order flow is not primarily driven by the dominance of certain subperiods in our sample, as shown by the rolling order flow coefficient estimates in Figure 5e. Third, the South Korean central bank is known to intervene frequently in the FX market, without disclosing any information about such activity publicly (Park, Chung, and Wang, 2001). Figure 6 plots the won together with the VXY. The won experienced a huge depreciation of roughly 40% following the collapse of Lehman Brothers. Figure 6 shows that this depreciation of the won may plausibly be a story of risk. One interpretation is that the South Korean central bank failed to intervene when market conditions deteriorated so sharply.

5 Summary

Prior to the development of the microstructure approach to FX, the study of exchange rates was in a state where nearly all possible explanations for explaining exchange rate movements appeared to be exhausted. Obstfeld and Rogoff (2001), and Flood and Rose (1995), concluded that the major drivers of exchange rates were not macroeconomic. However, the microstructure approach, and its use of data on the trading decisions by market participants, has provided some hope that we can move forward and find satisfactory models for these important macroeconomic asset prices. Order flow, the aggregate of trading decisions of initiators of foreign exchange transactions, has been shown to be capable of explaining a significant share of the movements in exchange rates. The problem, however, has been the difficulty of verifying these findings for a wide range of currencies over long sample periods. Typically, the sample length has either been rather short, or the coverage of different currencies has been limited. Sample lengths have varied from one week to eight years, with the majority being a few years or less. Although several currencies have been studied in the litera-

Figure 6
The South Korean won (KRW) and Risk



Note: The figure shows the South Korean won (KRW) quoted against the US dollar (USD) and the J.P. Morgan G7 Volatility Index (VXY), plotted from September 20, 2004 – June 24, 2011. The black vertical line indicates September 15, 2008, the day Lehman Brothers filed for Chapter 11 bankruptcy protection.

ture, the majority of these studies have been on major exchange rates —the euro, the Japanese yen and the British pound against the US dollar— and few on the currencies of Asia.

This paper is an examination of the longest data set on order flow studied to date, covering altogether eleven Asian and Australasian currencies (against the US dollar). Our data set includes all the major currencies of the Asia-Pacific region except the Chinese yuan. Specifically, we study the Australian dollar, the Hong Kong dollar, the Indian rupee, the Japanese yen, the South Korean won, the Malaysian ringgit, the New Zealand dollar, the Philippine peso, the Singapore dollar, the Thai baht and the New Taiwan dollar. To our, seven of these eleven currencies have never been studied before. Among these eleven are currencies under a purely floating regime, currencies that have changed regime over the sample, and currencies that have been fixed over the full sample. The length of our data enables us to study the impact of order flow over several financial crises. With data extending from January 1996 to October 2011, we can even study the impact of the recent sovereign debt crisis in Europe on these Asian and Australasian currencies.

We confirm previous results that order flow is a very strong predictor of exchange rate movements. This is especially true for floating exchange rates such as the Australian dollar and the New Zealand dollar. These results are sustained over the full 15-year sample, an indication that the impact of order flow is robust both to the choice of currencies (with different levels of liquidity) and the choice of periods. Currencies under a more fixed exchange rate regime also show a significant effect of order flow. The scope for such an effect is, of course, much narrower for credibly fixed regimes or successfully managed regimes than for floating exchange rates, but it is still a significant effect. Given the lower volatility of the currencies under these regimes, the effect of order flow is surprisingly strong. This is evidence that even if there is still a debate in the literature on the structural cause of an order flow effect, the effect is too strong and pervasive to be neglected by academics, policymakers and practitioners. In our regressions, we control for possible variables publicly available at the daily frequency, possible feedback trading effects, and predictability of flows (therefor, for liquidity disruptions), and find the same results independent of market liquidity levels. Since some of the currencies in our sample do not extend back to 1996 we derive a region-wide order flow measure based on principal component analysis, and find that a region-wide flow into the US dollar causes all currencies to depreciate (against the US dollar) when studied over the full 15-year sample.

Studying order flow over financial crises is important for at least two reasons. First, periods of turbulence in financial markets are the periods that we understand the least, and the documentation of order flow effects over these periods may prove useful to academics and policymakers alike. Second, they are also periods of great uncertainty, and it is exactly in periods of uncertainty that market participants have the greatest need for aggregating information. Hence, the impact of order flow as a vehicle for carrying information on dispersed beliefs can be expected to be at its largest during such periods. We indeed find that the impact of order flow is at its greatest during the financial crises in our sample, but the impact over more tranquil periods is not determined by such "outlier" events. The good news from our analysis for policy-makers is that the liquidity of markets has improved sufficiently over the 15 years, making markets more resilient to shocks.

This paper is an initial attempt to utilize a new and long data set on order flow, focusing on documenting the robustness of order flow and laying out a number of simple facts. Further research is clearly warranted, both on the relationship between order flow and macroeconomic variables, and the role of order flow during financial crises.

A Tables

Table 7
ADF-test of Exchange Rate Levels

	t-stat	p-value
AUD	-0.86	(0.80)
HKD	$-2.97*$	(0.04)
INR	-1.84	(0.36)
JPY	-0.99	(0.76)
KRW	$-3.13*$	(0.03)
MYR	-2.31	(0.17)
NZD	-1.13	(0.71)
PHP	-2.34	(0.16)
SGD	-0.94	(0.78)
THB	-2.44	(0.13)
TWD	-2.64	(0.09)

Note: Augmented Dickey-Fuller tests have been run using a constant. Optimal lag-length has been chosen using the Modified Akaike Information Criterion (MAIC). $**$ and $*$ denote statistical significance at the 1% and 5% levels, respectively. The sample length is January 8, 1996 – October 5, 2011.

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