Foreign Investor Feedback Trading in an Emerging Financial Market

Ingomar KROHN * Vladyslav SUSHKO † Witit SYNSATAYAKUL ‡

Abstract

This paper uncovers novel facts about trading behavior of non-residents in local financial markets and their impact on return dynamics and local investor trading, based on detailed regulatory order flow data in Thai foreign exchange, equity, and fixed income markets. First, foreign investors engage in positive feedback trading in all three asset classes, and their trading decisions resemble momentum trading rather than strong portfolio rebalancing activity between asset classes. Second, innovations to foreign investor order flow are informative of future returns, but the information is not based on local macro fundamentals. Third, local financial investors tend to mimic foreign investor trading, while non-financial investors consistently provide liquidity. Fourth, further tests suggest that the profitability of momentum trading is positively related to the amount of foreign capital flowing into the local financial market. Taken together, the results indicate that a significant presence of foreign investors can alter the trading behavior of local investors and can reduce the importance of local fundamentals in driving asset prices.

JEL Codes: F30, G11, G14, G15

Keywords: International financial markets, heterogeneous trading, disaggregated order flow, foreign investors, emerging markets.

This Version: November 2023.

We are grateful to Frank Packer, Andreas Schrimpf, Ilhyock Shim, Nikola Tarashev, Giorgio Valente, Paolo Vitale and the participants of BIS research seminar for helpful comments and suggestions. The views expressed in this paper are our own and do not necessarily reflect those of the Bank of Canada, the Bank for International Settlements, or the Bank of Thailand.

*Corresponding author. Principal Researcher, Financial Markets Department, Bank of Canada, IKrohn@bank-banque-canada.ca

†Senior Economist, Monetary and Economic Department, Bank for International Settlements, Vladyslav.Sushko@bis.org

‡Project Lead, Cross-Border CBDC, Bank of Thailand, WititS@bot.or.ths

1 Introduction

Emerging economy financial markets have seen a surge in cross-border capital inflows in more than a decade between the Great Financial Crisis (GFC) and the Covid crisis. Search for yields, low interest rates in advanced economies, and favourable global liquidity conditions combined with improving fundamentals have been behind this trend (CGFS 2021). Yet, due to limitations of publicly available data, research that leverages the precision of market microstructure data is still scant when it comes to studying the effects of foreign investors participation in financial markets of emerging economies.

This paper exploits detailed regulatory datasets on buy- and sell-transactions of different investor types in Thai financial markets. The comprehensive dataset allows us to shed new light on the differences in trading behavior *between* investor types, *across* asset classes, and *over* a long time period. In doing so, it provides new insights into the impact of foreign investors on local financial markets and on local investors' behaviour. A critical feature of the data is its coverage: comprehensive order-flow aggregated to daily frequency across different asset classes of an emerging market, i.e., order flow in the foreign exchange (FX), equity (EQ), and long-term fixed income (LD) markets. Due to strict reporting requirements, the dataset is free of any selection biases, and information is not just based on one trading venue or obtained from one brokerage firm, trading platform, or bank. Importantly, the dataset documents information on the type of participant that buys or sells any FX spot, equity or long-term fixed income product. This allows us to distinguish between trading behaviour of foreign investors and various types of local investors. The long daily time sample of more than ten years allows us to assess how the linkages between foreign and local trading behaviour have varied over time, and responded to local news releases.

Our findings can be summarized as follows. First, we document systematic differences between foreign and local investor order flow. Foreign investors appear to engage actively in feedback trading, i.e., a positive shock to asset returns is accompanied with significant contemporaneous buying pressure across asset classes, and vice-versa. To account for the contemporaneous correlation between returns and order flow, we employ an instrumental vector autoregression (VAR) framework, and show that the net demand for local assets lasts for longer than just the day of the initial shock. Further, we document that a sudden increase in foreign order flow, i.e., a positive net foreign demand shock, is highly persistent, indicating large and unexpected buy (sell) orders are followed by buying (selling) that persists for several days. In contrast, local investors appear to act in aggregate as liquidity providers, taking the opposite side of foreign investor trades. For example, Thai residents turn to net sellers following days of positive returns innovations.

Second, within local investors we identify substantial heterogeneity as to which types provide liquidity to foreign investors. More sophisticated local investors, those from the financial service sector, such as institutional investors, asset managers and local banks, tend to trade in the same direction as foreign investors, albeit with a lag. By contrast, the less sophisticated, non-financial market participants, such as corporates and retail investors, appear to consistently supply liquidity to the sophisticated investors. For instance, in response to positive return innovations, non-financial investors tend to sell Thai baht, equities and fixed income income securities, just as foreign investors are buying them. Which exact financial investors follow foreign investor trading, and which exact local non-financial investors take the opposite side, differs across the three financial markets.

Third, we infer the implications for informational efficiency by assessing whether foreign investors react differently to macroeconomic news release compared to local market participants. In line with trend-chasing behaviour rather than trading based on fundamentals, we find that the explanatory power of macroeconomic news surprises is substantially lower for foreign investor trading compared to local investors. Yet, foreign investor trading predicts future returns over medium horizons and the predictive power derives from transitory innovations in their order flow rather than the trend component, suggesting that foreign investor bring new information to local financial markets.

Fourth, we find evidence of short-term momentum trading by some investors, particularly in equity markets. Following Grinblatt & Keloharju (2000) we assess whether certain market participants follow short-term momentum trading, i.e., whether positive (negative) return realizations are followed by greater buying (selling). Sorting the order flow according to past return realizations, we find that, on average, foreign investors buy significantly more local assets following positive returns, and vice-versa. While this return chasing behavior is observable across markets, it is strongest when decision are only based on very recent return realizations and buy exceed sell orders most distinctively in equity markets. We also find no supporting evidence for the portfolio rebalancing motive for trading, a competing hypothesis studied in related literature. Further tests suggest that the returns to momentum trading as positively related to the amount of foreign investor capital inflow into the local financial markets.

Related Literature. This paper contributes to several strands of literature exploring heterogeneous trading dynamics among investors. First, a growing body of research tests for differences between foreign and local investors, focusing primarily on trades and order flow in a single equity market (e.g., Grinblatt & Keloharju 2000, Kim & Wei 2002, Agudelo et al. 2019, Ho 2022), with a small number extending the inquiry to a cross-country setting (e.g., Richards 2005, Froot et al. 2001). Similar to these papers, we find evidence for momentum-type trading in equity markets. Our findings are in line with Menkhoff et al. (2012), who document significant excess returns to FX momentum strategies in a cross-currency setting, with a portfolio skew towards minor currenies, i.e., those with limits to arbtirage, say, from FX controls. In addition, we find evidence of similar positive feedback trading in the FX and fixed income market by foreign investors. To assess the relationship between order flow and returns, we follow the instrumental variable approach in context of a VAR framework introduced by Danielsson & Love (2006). Similar to Breedon et al. (2021) we extent instrumental variable VAR setup to account for positive feedback trading when the data frequency is daily and order flow is observed separately for several types of investors.

Second, we add to the discussion on whether there are differences in the information set of foreign and local investors. For example, Brennan & Cao (1997) argue that foreign investors engage in momentum trading as they are less informed than their domestic counterparts, Choe et al. (2005) find that domestic investors trade on favourable prices, at least for some types of stocks, while Dvořák (2005) emphasizes the importance of local information and global expertise when comparing profits across investors and their investment horizons. Breedon et al. (2021) find that the temporary imposition of capital controls in Iceland had reduced the information content of krona trading and its responsiveness to news. From an intermediation perspective, Menkhoff et al. (2016) find that FX dealers aggregate private information from customer order flow. Adding to these studies, we employ an approach of Altavilla et al. (2017) to compute the loading of order flow of different types of investors on cumulative surprise components of macroeconomic announcements. While we consider macroeconomic news announcements, a related literature analyzes differences of equity trades around firm earning announcements, (e.g., Kaniel et al. (2012)). Even though foreign investors trade far less on macro news announcements compared to local inveostors, we find that innovations in foreign investor order flow are highly informative of future returns, not only in FX but also in bond markets. These findings are consistent with Hördahl & Valente (2022), who interpert the predictive power of international bond portfolio flows on EME exchange rates in the context of unique information about foreign investor preferences (i.e. risk premia) contained in their trading decisions.

Third, our paper relates to previous studies using regulatory data on investor trading in Thai financial markets. Koosakul & Shim (2021) show that trading volume in Thai local foreign exchange market is strongly influenced by currency volatility, with foreign end-customer trading volumes, in particular, rising significantly. Koosakul & Ananchotikul (2019) provide evidence that it is the non-resident, rather than resident, order flow that influences movements of the Thai Baht exchange rate. Examining dynamics across asset classes Gyntelberg et al. (2018) show that the impact varies across investors types, while Gyntelberg et al. (2014) assess portfolio rebalancing activity of investor for a period of two years before the financial crisis. In contrast to these papers, we examine heterogeneous trading behavior for a larger number of individual investor groups, across market segments and over a substantially longer time period. The more detailed and extended data sample provide insights as to how market participants adjust their investment decisions in response to the arrival of new information and across different macroeconomic regimes.

This paper proceeds as follows. Section 2 briefly discusses key aspects of Thai financial markets and introduces the dataset. In Section 4 we discuss the framework of the insturmental variable approach and assess the relationship between returns and different types of order flow. Section 5 concludes the discussion.

2 Data

Order flow dataset. We utilize a comprehensive regulatory dataset that tracks the trading behavior of investors across major asset classes - equity, fixed income, and foreign exchange - over ten years between January 2011 and August 2020. The unique and granular data is obtained from the Thailand Stock Exchange Market (SET), the Thai Bond Market Association (TBMA), and the Bank of Thailand (BoT). It has at least four merits that are worth highlighting and stand out compared to previous research on foreign investor trading dynamics.

First, the combination of sources includes all executed transactions in foreign exchange (FX), equity (EQ), and long-term fixed income markets (LD) providing a holistic account of investment flows in an emerging market. Second, reporting requirements by the three institutional bodies ensure that all trades are precisely tracked and documented. Hence, the data is free of any reporting biases that may exist in commercially available datasets that are based on a subset of trades from individual platforms or provided by a subset of market participants. Third, information on buy and sell orders is documented at the disaggregated level for various types of investors, i.e., we can assess differences in investment flows from local and foreign investors, who purchase and hold different Thai baht-denominated assets as part of their portfolio. Finally, in contrast to previous studies on heterogeneous investor trading dynamics, our dataset comprises a substantial number of daily observations, i.e., it spans close to ten years (2358 days) of trading during the post-global financial crisis period. The long daily time sample allows us to analyse trading behavior over long horizons and to assess trading around specific events (e.g., news announcements) or under different regulatory regimes. In sum, the database enables us to shed new light on the differences in individual trading behavior *between* investor types, *across* asset classes, and *over* an extended period.

To analyze heterogeneous investor behavior, we construct disaggregated trading volume and order flow measures for the following groups of domestic market participants: institutional investors (IT) – comprising insurance companies, government funds, and other financial institutions – asset managers (AM) – comprising private mutual funds and securities companies – non-financial corporates (CO), banks (BA), and individual retail investors (RE). We classify the aggregate of volume and order flow from these groups as "local investor" (LC).[1] In addition, we observe information on foreign investor trading (FO), i.e., we are able to identify separately the purchase and sell orders of non-resident market participants.

[1]Not all investor groups are active in all asset classes. We do not observe trading from banks in FX and equity, from non-financial corporations in equity, and from retail investors in fixed income markets.

For every investor group j we construct order flow at the daily frequency t in asset class c as

$$OF_t^{j,c} = BUY_t^{j,c} - SELL_t^{j,c},$$

and total daily trading volume as

$$VOL_t^{j,c} = BUY_t^{j,c} + SELL_t^{j,c},$$

where $BUY_t^{j,c}$ ($SELL_t^{j,c}$) measures the aggregated intraday buy (sell) orders on day t. Volume and order flow are both measured in millions of U.S. dollars. Positive net order flow indicates that buy orders of Thai currency, equities, and fixed income assets exceed sell orders. Combining these two measures, we calculate normalized order flow as the ratio of order flow and volume in order to account for the different price impact of trading decisions relative to the prevalent level of liquidity i.e.,

$$NOF_t^{j,c} = \frac{OF_t^{j,c}}{VOL_t^{j,c}}.$$

Summary Statistics. Figure 1 shows the developments of trading volume over time, across asset classes, and by investor group. The left panels display total trading volume (indexed to 100 in January 2011) and distinguishes between trading activity of foreign (navy) and local investors (teal). The right panels show the relative trading volume, i.e. the proportion each investor group contributes to total trading volume.[2]

[INSERT FIGURE 1 HERE]

Foreign investors have accounted for the majority of trading volume in FX markets for all the years in our sample period apart from 2014, when their participation declined following the 2013 “taper tantrum” (Figure 1, panel A, left). Among local FX market participants, corporates represent the largest sector (panel A, right), which is typical of emerging markets where financial institutions have a smaller presence in FX markets compared to advanced economies.

[2] Table A-I in the Online Appendix provides further details on trading volume by investor group.

In equity markets, by contrast, foreign investor trading volumes used to significantly lag those of domestic investors, but have grown and caught up with local investors over the last three years or so of the sample period (Figure 1, panel B, left). Among local investors, retail trades represent the most active segment in equity market trading by volume (panel B, right).

Finally, foreign investor participation is lowest in local long-term bond markets, accounting for about 20% (Figure 1, panels C, left). Among local investors, banks, followed by asset managers and institutional investors, account for virtually all of the trading volumes by residents in local long-term fixed income markets (panel C, right).[3]

Table 1 shows summary statistics for returns (Δs) and normalized order flow (NOF). A key observations is that while returns are random and unpredicatble, order flow appears to be not random and predictable. Specifically, returns across three markets are noisy at the daily level, and on average not significantly different from zero. For equity and fixed income markets, however, we note that the median is positive and significant (4.99 basis points (bps) and 0.27bps). In terms of order flow, the table confirms that foreign investors are on average net buyers of local assets, while some local investors are on average net sellers, and all local investors are on average net sellers of local currency in the FX market. For example, on average there exists Thai-denominated assets excess buying of non-residents in the foreign exchange, equity and bond markets, as indicated by the positive normalized order flow of 0.08, 0.01, and 0.08, respectively. Local investors in FX primarily sell local currency on average (-0.09), while they buy local assets in equity and bond markets (0.01 and 0.09, respectively). Between locals, institutional investors, asset managers, and corporates are more likely to sell Thai Baht (on average), while retail investors are more likely to buy the currency. The excess buy orders, however, are only a third of the size compared to foreign investors in the FX space. In equity and fixed income market, institutional investors have similar or even larger buy orders (0.2 or 0.21) than foreign investors, and exceed those of other local trading groups.

[INSERT TABLE 1 HERE]

[3]Note that the order flow of the official sector is not included in our dataset. Hence, the Bank of Thailand currency operations are missing, as well as primary market activity in Thai government bonds.

3 Empirical Anlaysis

The previous section highlights systematic differences in trading dynamics across different market participants. This suggests the relationship of order flow with returns also differs by investor types. We follow the market microstructure literature and employ vector autoregression (VAR) models to study the relationship between returns and order flow. As described below, we explicitly take into account contemporaneous feedback effects when we evaluate the relationship between flows and price changes.

3.1 VAR setup

Following an extant empirical literature, we assess the relationship between order flow and returns in a VAR framework, where y_t is defined as $y_t = [R_t, NOF_t]'$, R_t refers to the log return for an asset on day t, and NOF_t is the normalized order flow during the same period. With aggregated normalized order flow, the VAR specification can the be expressed as

$$y_t + Ay_t = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j} + \varepsilon_t,$$

where in this general case of aggregated order flow, y_t is a 2×1 vector at time t, comprising returns and normalized order flow, α contains intercept terms, and y_{t-j} are lagged variables up to p lags. Further, A is a 2×2 matrix, such that

$$A = \begin{bmatrix} 0 & -a_{12} \\ -a_{21} & 0 \end{bmatrix}$$

and a_{12} captures the contemporaneous impact of normalized order flow on returns, while a_{21} measures the effect of returns on normalized order flow. A particular challenge in our framework are potential feedback effects due to the relatively low sampling frequency at the daily level, i.e., we need to take into account that market participants react to intraday price changes and adjust their buy and sell orders within the day. This particular challenge implies that we explicitly consider the case where $-a_{21} \neq 0$, meaning that there can be a contemporaneous impact of returns on normalized order flow, and exploiting the ordering of the VAR variables to model the linkages within the estimation system is not possible. Instead, following Danielsson & Love (2006) we use an instrumental variable approach to make inferences about the relationship between the variables.[4] The authors suggest to stack the exogeneous and endogeneous variables in one vector, such that

$$y_i = z_i \Pi_i + \epsilon_i, \text{ i=1,2}$$

where Π_i is a $(1+k) \times 1$ parameter vector, y_t contains the endogeneous variables (i.e., $y_{it} \in R_t, NOF_t$) and together with ϵ_i are vectors of length $T \times 1$. Importantly, z_i is a matrix of the size $T \times (1+k)$, containing the vectors of instruments z_{it}. Danielsson & Love (2006) suggest to express the system in matrix form written as,

$$\underbrace{\begin{bmatrix} R \\ NOF \end{bmatrix}}_{Y} = \underbrace{\begin{bmatrix} z_1 & 0_{T\times(1+k)} \\ 0_{T\times(1+k)} & z_2 \end{bmatrix}}_{Z} \underbrace{\begin{bmatrix} \Pi_1 \\ \Pi_2 \end{bmatrix}}_{\pi} + \underbrace{\begin{bmatrix} \epsilon^R \\ \epsilon^{NOF} \end{bmatrix}}_{\epsilon}$$

with the dimensions: Y is $2T \times 1$, Z is $2T \times 2(1+k)$, π is $2(1+k)$, and ϵ is $2T \times 1$. The system can be estimated using conventional two-stage least square estimator, in order to account for the contemporaneous relationship between R_t and NOF_t.

Since we observe order flow for different groups of market participants, we extend the approach outlined above to account for the heterogeneity between investor types. This modelling approach is similar to Breedon et al. (2021), who assess the differences between dealer and central bank order flow. Our analysis begins by distinguishing between foreign and local investors, i.e. we define y_t^c as

$$\begin{aligned} y_t^c &= [r_t^c, NOF_t^{c,FO}, NOF_t^{c,LC}] \\ &= [r_t^c, \boldsymbol{NOF_t^c}] \end{aligned}$$

[4]The authors document that returns and order flow in the foreign exchange market co-move contemporaneously, leading to noticeable feedback effects, unless the data is sampled within seconds. Only when data is sampled at these high intraday frequencies, is the assumption of $a_{21} = 0$ valid. In otherwise liquid markets, one needs to consider timely price changes to buy- and sell-decisions.

This implies that A_0 extends to a 3×3 matrix, i.e.,

$$A = \begin{bmatrix} 0 & -\beta_{FO} & -\beta_{LC} \\ -\gamma_r & 0 & -\gamma_{LC} \\ -\delta_r & -\delta_{FO} & 0 \end{bmatrix}$$

where β_{FO} (β_{LC}) measures to the contemporaneous impact of foreign (local) investors on returns, γ_r and γ_{LC} capture the contemporaneous impact of returns and local normalized order flow on foreign normalized order flow, and similarly δ_r and δ_{FO} measure the impact on local trading decisions.

As common in the literature, we then calculate impulse response functions (IRFs) in order to assess the informativeness of trade decisions from different groups of market participants. To this end, we express the VAR model in terms of a standard VMA representation, i.e.,

$$\boldsymbol{y_t} = \Psi(L)\boldsymbol{\epsilon_t}$$

where $\Psi(L)$ measures refers to a $n \times n$ lag polynomial and $\boldsymbol{\epsilon_t}$ are the structural shocks.

3.2 Instrumental Variable Estimation

Since there exists little theoretical guidance on the choice of instruments, we largely follow modelling approaches in previous papers to instrument the dynamics of the endogeneous variables. The instruments used for each equation of the baseline VAR estimation are summarized in Table 2.

[INSERT TABLE 2 HERE]

Panel A documents the endogeneous variable in the second stage regression (column: "2.Stage"), the variables that need to be instrumented in the first stage regression ("1.Stage"), and the instruments that are employed ("Instruments"). The sets and number of instruments vary across asset classes and between the equation, and are chosen as set of reasonable instruments when statistical tests point towards their validity and independence of the instrumented variable (Panel D). The following instruments are considered as part of the modelling approach. First, for each asset class, we include up to five additional lagged days of returns (e.g., Δ s_{t-j}^{FX}) and normalized order flow (e.g., $\mathrm{NOF}_{t-j}^{FX,LC}$) components to exploit the serial correlation of these variables (Danielsson & Payne

2002). Second, we include lagged foreign order flow and aggregated local order flow from other asset classes, in order to capture similar trends that can be observed across asset classes. For example, when instrumenting foreign and local normalized order flow in equity markets, we employ lagged normalized order flow from foreign exchange market ($\mathrm{NOF}_{t-j}^{FX,FO}$, $\mathrm{NOF}_{t-j}^{FX,LC}$), to account for the fact that demand dynamics are correlated across markets. Further, following Breedon et al. (2021) who analyse Icelandic foreign exchange market order flow, we include lagged values of credit default swap (CDS) spread on Thai government bonds, and a synthetic Thai Baht against the euro exchange rate (Δ s_t^{THBEUR}). While this variable enters also contemporaneously, triangular arbitrage is less concerning as the currency pair is not actively traded against both the U.S. dollar and the euro and, further, the considering comparatively low trading volume of Thai Baht during mainly U.S. overnight hours is unlikely to affect price dynamics between the U.S. dollar-euro rate significantly. In addition, we also include lagged one-week FX options risk reversals (RR_{t-j}^{1W}), as these derivatives contracts are suited to capture short-term market expectations. Finally, we construct equally weighted portfolios ($\Delta \mathrm{s}_{t-j}^{EW}$) of foreign currency, equity, or fixed income returns from emerging markets in the same geographical area or we consider lagged return dynamics from markets of other regional economies, such as Singapore (Δ s_{t-j}^{SG}) or Japan (Δ s_{t-j}^{JP}), in order to account for regional trends that may spill over to the Thai economy.

Panel D of Table 2 shows regression diagnostics of the instrumented variable regressions, providing evidence that the chosen instruments are statistically valid. For each asset class and instrument, we document the p-value of a F-test to assess the joint significance of the variables chosen as instruments (p-val$^{Instr.}$). In most cases, these p-values indicate the sets of instruments are jointly significantly different from zero, ranging between 0.00 and 0.06. The only exception to this are the instruments for equity returns (p-value: 0.20) and local order flow in bond markets (p-value: 0.19). Further, we report p-values of Hansen's J statistic ("J-stat"), testing the null hypothesis that the instruments are valid, and of the C-test whether the chosen instruments can be considered as exogenous ("End."). With respect to validity, the p-values suggest the null-hypothesis can never be rejected at the 5%. The lowest p-value is 0.05 in case of $\Delta \mathrm{s}^{FX}$ and reaches 0.53 for $\Delta \mathrm{s}^{EQ}$, never rejecting the null hypothesis at a relevant statistical level, that the instruments are valid. Similarly, high p-values of the C-test (ranging between 0.10 and 0.98) provide statistical support that the instruments can be considered to be exogenous.

Table 3 next shows the estimated contemporaneous coefficients of the second stage regressions and provides first insights into the relationship between returns and disaggregated order flow dynamics. For example, the table points towards a positive significant contemporaneous relationship between foreign investor buying pressure and returns across all asset classes. In foreign exchange and fixed income markets, the coefficients are highly statistically significant, while they remain comparably small in equity markets. In contrast, local investor excess buying is negatively correlated with foreign investor order flow in foreign exchange (-0.35) and equity markets (-2.77), while it is insignificant in fixed income markets (-1.02). Overall, the table is indicative of heterogeneous linkages between foreign and local investors, and return dynamics. These are further explored using impulse response functions in the next section.

[INSERT TABLE 3 HERE]

3.3 Impulse response functions: Foreign and Local Investors

We use impulse response function to document the relationship between returns and order flow. First, we focus on the response of individual order flow components to changes in returns. The response in each asset markets are shown in Figure 2 to 4 .

[INSERT FIGURE 2 to 4 HERE]

Following a one-unit shock to FX returns (panel A), there is an immediate on impact increase in foreign investor FX buying pressure of 0.25%. The increase in demand persists to the next day, before reversing slightly thereafter. In equity markets (panel B), the response of foreign investor buying to a positive returns shock is smaller in magnitude on impact (slightly above 0.01%), but it is more persistent. It increases to close to 0.03% during the subsequent day and decaying at a much slower pace than trading in FX, remaining positive and significant for close to two weeks. In fixed income markets (panel C), the initial buying pressure in a response to a positive returns shock is close to 0.12% and decays slowly over the course of a business week.

In contrast to foreign investors, the local investors respond to a positive returns shock by selling the asset, be it Thai baht, equities, or bonds. Specifically, in response to the positive return shock in the FX, equity, and fixed income market, the same-day local investor normalized net order flow is -0.12%, 0.025%, and -0.21%, respectively.

Figure 3 shows the impulse responses of returns and local investor order flow to a one-unit shock to foreign order flow. Focusing on the left panels first, a positive shock to foreign investor order flow is associated with higher returns in all three markets, which are sustained for at least two days, and up to three to four days in the case of FX and bond returns. The right panels of Figure 3 show the responses of local order flow to a foreign order flow shock. In the FX market, a one-unit increase in net foreign order flow is associated with an immediate net selling of almost 0.05% of daily trading volume by local investors, and a further persistent selling which remains significant over a two-week period. In equities, a one-unit increase in net foreign order flow is associated with an immediate strong net selling of over 0.2% equivalent, and a further persistent net selling thereafter. In local bond markets, a positive shock to foreign investor net order flow shows only a brief response in local trading, which decays in less than a week to it's initial level.

Lastly, Figure 4 shows the response to innovations in local order flow. Complementing the previous figures, the response of returns in foreign exchange market is weak and barely significant. In equity markets, returns decline sharply by 4% but decays within a couple of days. Only in fixed income markets, we observe a positive response to an increase in local buying pressure, though the impact of 0.25% is comparatively small.

All-in-all, the IRF analysis suggests that local investors, in aggregate, tend to provide liquidity to foreign investors in the FX and equity market, with foreign investors trading in the direction of future return dynamics.

3.4 Impulse Response Functions: Disaggregated Local Order Flow

The aggregate impluse responses of local investor order flow mask the significant hetergeneity in trading behavior among different local investor types. In order to examine these differences within the same VAR setting, we replace the aggregate local order flow with its individual components, which extends the y_t to a vector containing the returns in asset class c and up to six measures of order flow. For example, for FX market dynamics, the y_t^{FX} would be defined as

$$\begin{aligned} y_t^{FX} &= [r_t^{FX}, NOF_t^{FX,FO}, NOF_t^{FX,IT}, NOF_t^{FX,AM}, NOF_t^{FX,CO}, NOF_t^{FX,RE}] \\ &= [r_t^{FX}, \boldsymbol{NOF_t^{FX}}] \end{aligned}$$

Figure 5 shows impulse responses of disaggregate local investor order-flow to a positive one-unit deviation shock to returns, while Figure 6 shows the response dynamics to a one-unit deviation increase in foreign net demand.

[INSERT FIGURE 5 to 6 HERE]

Although the precise IRF results and their significance differs across the three financial markets, overall, especially in the FX and equity markets, impulse responses indicate that local financial investors tend to follow foreign investors in their tradign behavior, while local corporates and retail investors provide liquidity to the former. More precisely, local financial investors, comprised of institutional investors and asset managers, tend to follow a similar trading pattern to that of foreigner investors, but with a lag. By contrast, corporates and retail investors tend to trade in the opposite direction.

In the FX market, asset managers exhibit positive purchases beginning on the immediate day of in response to both the returns and foreign investor order flow shocks (Figures 5 and 6, panel A). At the same time, the IRFs of corporate and retail order flows are negative and statistically significant in response to both types of shocks (panel B). The selling by both investor groups persists for at least one day, and possibly two, in response to the shock. Thus, the results corroborate the traditional wisdom in that local corporates constitue natural counterpaties to foreign trades in local currency, as they require less local currency for the same value of U.S. dollar trade receipts when local currency appreciates, and vice-versa. Retail trades also seem to provide FX liquidity to foreign traders in local currency markets, perhaps relfecting the conventional wisdom that retail traders constitute less informed liquidity providers, meeting the liquidity demand of the informed sophisitcated traders, as in the traditional Kyle model.

In the equity market, local asset managers investors tend to be net buyers in response to a positive shock to returns (Figure 5, panel C). At the same time, in response to positive foreign investor net demand shock, local financial investor trading diverges somewhat, with asset managers seeming to follow foreign investor buying, and local institutional investors remaining net sellers in aggregate (Figure 6 panel C). Retail investors exhibit persistent selling following a positive returns shock and appear to provide liquidity (sell equities) following a positive foreign investor net demand shock (Figures 5 and 6, panels D).

In local bond markets, asset managers exhibit persistent buying in response to a positive shock to returns and to foreign investor net order flow while institutional investors exhibit net selling. Local banks, likely reflecting their role as broker dealers, also sell in response to a positive bond returns shock, and also sell in response to a positive foreign investor net demand shock. In both cases, bank impulse response are not persistent, with significant buying lasting for only one day.

4 Foreign Investor Trading Under The Microscope

While the previous analysis points towards a strong positive contemporaneous relationship between foreign investor order flow and prices in all asset classes, in this section we further examine the dynamics of foreign investor trading decisions in respect to the two dimensions. First, we provide additional evidence suggesting that the documented positive price impact are in line with foreign investors being better informed market participants than local investors. Second, we examine whether foreign investor trading resemble portfolio rebalancing dynamics or rather point towards momentum and feedback trading. We show the data suggsts evidence in favor of the latter trading approach.

4.1 Are Foreign Investors Better Informed?

4.1.1 Disaggregated Order Flow: Predictive Regressions

The instrumental VAR analysis highlights a positive contemporaneous returns between returns and normalized order flow of foreign investors. Next, akin to Lundblad et al. (2022), we assess whether investment decisions of foreign market participants are long-lived and impact prices for more than on day. To this end, Table 4 reports results from predictive regressions between foreign or local normalized order flow and cumulative future returns.[5] Across columns, we report the cumulative returns in each market following the day of the investor's trading decision. For each market, we consider return horizons between 1-day and 1-month.[6]

[INSERT TABLE 4 HERE]

First, the predictive power of foreign investor normalized order flow ranges between 1-day in equity markets, and up to 1-week in foreign exchange markets. In the FX market, a one standard deviation increase net foreign buying pressure is associated with 0.8 standard deviation higher Thai baht returns on the following day, with the positive predicitve effects lasting for four additional trading days (Table 4, panel A). In fixed income markets, the magnitudes of foreign order flow predictive power for future returns are slightly larger than those in FX, but shorter lived, turning insignificant after two days (Table 4, panel C). In equity markets, clear significant predictive power of order flow for equity market disappears after the first day (Table 4, panel B). This might be consistent with lower information content of equity market order flow, as gleaned from its low loading on news announcements (see Section 4.1.3, below), but could be also driven by the fact that we can only observe the aggregate trading decisions of the SET, but not that of individual stocks. Second, in contrast to foreign normalized order flow, local market participants' investment decision do not contain any predictive power across markets. The estimated coefficients are either not statistically different from zero (FX, LD) or even negative (EQ), i.e., large net demand is associated with persistent depreciation of equity returns. Overall, the persistent price impact of order flow is consistent with the interpretation that foreign investors contain superior information about price dynamics that realize subsequent to their trading decision.

4.1.2 Price pressure and demand shocks

To provide further evidence of information asymmetries between foreign and local investors, similar to Gompers & Metrick (2001) and Ferreira et al. (2017), we decompose normalized order flow in a trend and shock component to identify whether returns are driven by daily portfolio

[5] We report results from predictive regressions with local order flow as explanatory variable in Table A-II in the appendix.

[6] We measure the return horizon by the number of trading days, i.e., 1-week, 2-weeks, and 1-month refer to 5-, 10-, and 21-days, respectively.

decision or long-term trends. Specifically, we follow Lundblad et al. (2022) and proxy market-wide long-term demand trend as a moving-average over the previous 1-month, 3-months and 6-months up to day $t-1$, and subtract it from order flow on day t to measure temporary investor demand that is likely driven by informational advantages. Once we decomposed normalized order flow in both components, we estimate one-day ahead predictive regressions and tests whether the predictive power stems from the persistent or temporary component.

[INSERT TABLE 6 HERE]

The results in Table 6 indicate that the predictive power of foreign investor order flow is primarily coming from the transitory component. The coefficients associated with the transitory component are all positive - ranging between 0.8 and 0.10, and highly statistically significant. In contrast, coefficients of the permanent component are all positive too but generally smaller in magnitude and not statistically different from zero. These results are robust to the length of the window that was used to calculate the moving-average. For local investors, coefficients are largely not different from zero and most often show a negative sign for both the transitory and permanent component. The predictive power of foreign investors' transitory order flow component suggests that trading decisions independent of momentum trading have a signficant impact on prices, i.e., if foreign investors are better informed and invest in assets unrelated to long-term trends, it has a significant impact on returns across asset classes.

4.1.3 News Surprises and Order Flow Dynamics

The analysis so far focused on the dynamics between returns and order flow. In this section, we measure the extent to which new information about macroeconomic fundamentals contributes to these dynamics. The results will show that new information about macroeconomic fundamentals explains far lower proportion of foreign investor order flow compared to local investor order flow. This is in line with the results in the previous sections that showed that foreign investor order flow, especially in FX and equity markets, exhibits time-series momentum and is characterised by positive feedback trading. By contrast, local investor order flow exhibited heterogensity across investor types and key asset classes. Hence, predictably, a lower share of foreign investor trading is explained by macro fundamentals compared to local investor trading.

Methodologically, we follow the approach by Altavilla et al. (2017) by constructing a news-riven order flow index, then examining its loading on actual order flow at different frequencies. The approach can be summarized as follows.

First, we construct a local news index of macroeconomic surprises. We collect information on expected and realized local macroeconomic announcements from Bloomberg's Economic Calendar. We focus on the most relevant news announcements for which survey expectations are available.[7] These announcements include interest rate decisions by the Bank of Thailand, inflation and other price dynamics (e.g., CPI YoY) , as well as trade-related statistics (e.g., Customs Imports YoY). Second, we run the following first-stage regression:

$$NOF_t^c = \alpha + \sum_{i=i}^{n} \beta_i^c news_{i,t} + \varepsilon_t^c, \tag{1}$$

where NOF_t^c denotes daily disaggregated normlized order flow, α a constant term, $news_{i,t}$ is the surprise component of news release pertaining to macro statistic i.

Macroecononmic news surprises are defined as the difference between the realized data and the survey forecast, i.e., positive news implies the released macroeconomic data was more positive than expected by market participants. On days when no announcement takes place, no news are released and $news_{i,t} = 0$.

Using the results of the regressions based on Eq. 1, we follow Altavilla et al. (2017) and constrcut the daily news-driven order flow (D) index using the fitted values from Eq. 1, i.e., $nix_t^{D,c} := \widehat{NOF_t^c}$.

Next, we aggregate daily order flow to lower frequencies to use them in the estimation of the cumulative effects of new information about macro fundamentals. We denote low-frequency order flow as $NOF_t^{h,c}$, where $h \in \{W, M, Q\}$ refers to daily order flow that is aggregated to the weekly, monthly and quarterly frequency, respectively. In the same vein, we aggregate the daily news index to the same frequencies, i.e. $nix_t^{h,c}$ for $h \in \{W, M, Q\}$, to estimate the following low-frequency regression:

$$NOF_t^{h,c} = \kappa^{h,c} nix_t^{h,c} + \mu_t^{h,c}, \tag{2}$$

[7] We rely on Bloomberg's Relevance Indicator to identify announcements that are at important for a particular market by at least 50% of survey respondents.

where $\kappa^{h,c}$ captures the loading of different investors on the news-driven order flow index at different frequencies.

Of main interest is the explanatory power of these regressions. Figure 7 shows the results. There is a systematic difference in the explanatory power of news for foreign investor order flow compared to local investor order flow. Across all frequencies and asset classes, the adjusted $\bar{R}^2$ in the foreign order flow regressions is lower. For instance, in the FX market, at a weekly frequency, about 20% of foreign investor order flow can be explained with macro news arrivals, compared to about 60% of local investor order flow. At a quarterly frequency, the explanatory power of fundamentals news rises to about 70% and 80%, respectively. In the fixed income market, the higher share of variation in foreign investor order flow is driven by fundamental news surprises, about 50% at a weekly frequency and more than 70% at a quarterly frequency. The share of foreign investor order flow in fixed income market also tend to rise closer to that of local investor order flow as the frequency drops. This can be interpreted as a cumulative effect fundamental information on trading decisions of investors. Finally, the same patterns hold for the explanatory power of macro news for foreign and local investor order flow in the equity market, however the magnitudes are much smaller. This is likely because firm specific news, such as earnings announcements, are at least as important as macroeconomic fundamentals in driving investors' trading decisions in equities.

[INSERT FIGURE 7 HERE]

4.2 Foreign Investors and Portfolio Allocation

While the previous section suggests that foreign investors have an informational advantage compared to their local counterparties, we next aim to better understand their trading approach. In particular, we test whether order flow dynamics can be associated with active portfolio rebalancing (e.g., Hau & Rey (2005)) or whether investment decisions are in line with time-series momentum trading and return chasing.

4.2.1 Portfolio Rebalancing

To assess portfolio rebalancing activity, we follow Hau & Rey (2005) and Gyntelberg et al. (2014) and test whether foreign investor activity in local asset markets (equity and fixed income) are associated with an appreciation of the Thai baht. In line with increasing demand for local assets and corresponding need to obtain or hold local currency, one would expect the Thai baht to appreciate. Second, higher returns in the Thai equity and fixed income markets, relative to the U.S., should be associated with net sales of foreign positions (negative order flow) as investors aim to have a constant country exposure and decreases their position due to the positive wealth effect (Hau & Rey (2005), Brennan & Cao (1997)). Third, and relatedly, these portfolio re-allocation and selling pressure from local equity and fixed income order flow show be reflected in a depreciation of the Thai Baht.

Table 5 reports the results from assessing these hypotheses for the equity (left panel) and bond (right panel) markets, separately. Focusing on the first column in each market, Table 5 suggests that an increasing demand for local equities and bond markets is associated with an appreciation of the Thai baht. It is evidence that foreign investors demand local currency to purchase local assets, and points towards the close link across asset classes. Focusing on the second column, we find that an increase in local returns relative to global returns (as proxied by returns on the SP500 and 10-year U.S. government bonds) is associated with further foreign demand. Contrary to portfolio rebalancing, foreign investors increase their local positions and don't scale back in order to compensate wealth effects of their global portfolios. This line of argument is supported by the results in the last columns, which show that return differential between local and foreign markets are not associated with a depreciation of the Thai baht, i.e., if foreign investors were selling local equity/bond positions to reinvest in other markets, one would expect the Thai currency to depreciate. However, this is not the case and, in fact, high return differentials are even associated with an appreciation of the baht. Taken together, these findings don't suport conventional hypotheses related to portfolio rebalancing of foreign investors.

[INSERT TABLE 5 HERE]

4.2.2 Momentum Trading

Since the previous section suggets that evidence in favour of portfolio rebalancing is rather weak, we next address whether foreign investor trading can be systematically categorized as investments that follow conventional momentum strategies. To this end, we follow Grinblatt & Keloharju (2000) to assess how different investor groups buy and sell assets in response to past return dynamics. In a conventional time-series momentum strategy, investors hold a "long" position following positive returns , and a "short" short position following negative returns. Hence, we allocate daily order flow to either a hypothetical long and short portfolio, according to the past returns realizations, and then calculate the average difference between buy and sell orders from these two portfolios. To account for the persistent impact of returns on investment decisions, we calculate cumulative past returns over different horizons: the previous day [-1,1], the past two days [-2,1], the previous week [-5,1], and the past two weeks [-10,1]. Figure 8 shows the unconditional test results for time-series momentum extended to different look-back periods.

[INSERT FIGURE 8 HERE]

The positive FO bars indicate that foreign investors tend to further increase their holdings following positive returns across all three asset markts. Panel A shows that foreign investor momentum trading in the FX market, while singificant in magnitude, is farily short-lived, falling off rapidly after two days. Panel B shows even larger momenturm trading by foreign investors in equity market. Time-series momentum of foreign investor order flow in equities is also highly persistent, remaining significant for look-back periods beyond 10 days. Hence, our results, obtained from a longer sample period and with a different methodoloy, constrast with those of Gyntelberg et al. (2012), who find evidence in favour of foreign investor portfolio rebalancing rather than momentum trading in Thai equity market. Panel C shows smaller in magnitide but also persistent time-series momentum of foreign investor order flow in fixed income markets.

Figure 8 also confirms heterogeneous trading behavior by different types of local investors. In the FX market, local investor order flow exhibits hardly any time-series momentum, except for some small momentum trading by local institutional investors. Foreign investor momentum trading is initially accomodated by local corporates and retail investors, but those are exceeded by local asset managers for longer look-back periods [-5,1] and [-10,1] (Panel A). In the equity market, local financial investors add to foreign investor momentum trading, with local retail investors accommodating momentum trading by all other investor groups (Panel B). In the fixed income market, local asset manager order flow exhibits time-series momentum about equal in magnitude and persistency to that of foreign investors (Panel C). Local institutional investors accommodate momentum trading in fixed income markets by the former investor groups.

4.2.3 Momentum Trading and Profitability

Since average order flow dynamics of foreign investors appear to follow momentum-style trading, we next assess the average profitability over time of such a trading approach. To this end, we allocate daily returns on day $t+1$ to a long (short) portfolio, following positive (negative) order flow over different formation periods (e.g., over days $t-5$ to t). The top row of Figure 9 shows the average yearly returns, while the bottom panel illustrates profits to a hypothetical investment of $1 at the beginning of the sample period.

[INSERT FIGURE 9 HERE]

Figure 9 shows that in the foreign exchange market the momentum trading strategy only starts to generate consistently positive returns from 2016 onwards. In equity markets, there are positive return developments in the first three years of the sample, followed by a sharp decline up until 2017, and strongly volatile return dynamics thereafter. In fact yearly returns are effectively zero for most of the latter years, as suggested by the middle graph in the top row. In fixed income markets, momentum trading appears unprofitable in the first few years of the sample, with increasingly steeper profits from 2016 onward.

The results suggest that returns of an average momentum trading strategy are volatile and appear to be closely related to both local and external developments. For example, returns to momentum trading in the FX market increased in 2015 onwards. It is noteworthy that this is roughly the time when FX controls were relaxed substantially. Specifically, the non-resident baht account (NRBA) limit (the amount of local currency non-residents could effectively borrow from financial institutions without an underlying exposure) increased from 300 million to 600 million THB, effective May 2015. In equities, in turn, momentum returns declined sharply in 2013, around the time of the June 2013 Taper Tantrum. And, there is a sharp decline and a bounce-back of momentum returns in both FX and equity markets around the 2020 Covid-19 financial turbulence. All-in-all, returns to momentum appear to be associated with the amount of foreign investor capital flowing into local financial markets.[8]

5 Conclusion

This paper utilizes a detailed regulatory dataset of order flow of different types investors in Thai foreign exchange (FX), equity, and fixed income markets to study the effects of foreign investor trading on financial markets of an emerging economy.

Foreign investors appear to engage actively in feedback trading, and their trading predicts future returns. In fact, there is strong evidence for momentum trading by foreign investors, while we find no support for portfolio rebalancing trading motive. Additional tests suggest that the profitability of monentum trading is positively related with the amount of foreign capital flowing into the local financial markets.

Price impact of foreign investor trading is also persistent, and points at informed trading. Specifically, the predictive effects of foreign investor order flow derives from transitory innovation to their order flow, rather than the persistent component. At the same time, new information about local macroeconomic fundamentals explains lower share of foreign investor trading compared to local investors.

While in aggregate local investors provide liquidity to foreign investors, their trading behavior is also quite heterogeneous. More sophisticated local financial investors, such as institutional investors, asset managers and local banks, tend to trade in the same direction as foreign investors, albeit with a lag and differences across asset classes. This suggests that foreign investor participation in local financial markets can alter the trading behaviour of some local investors. By contrast, the less sophisticated, non-financial market participants, such as retail investors, appear to consistently supply liquidity to the more sophisticated investors. Not surprisingly, local corporates also serve as natural counterparties to foreign investors in the FX market.

[8]We report summary statistics of such a strategy in the appendix in Table A-IV.

References

Agudelo, D. A., Byder, J. & Yepes-Henao, P. (2019), 'Performance and informed trading. comparing foreigners, institutions and individuals in an emerging stock market', *Journal of International Money and Finance* **90**, 187–203.

Altavilla, C., Giannone, D. & Modugno, M. (2017), 'Low frequency effects of macroeconomic news on government bond yields', *Journal of Monetary Economics* **92**, 31–46.

Breedon, F., Pétursson, T. G. & Vitale, P. (2021), The currency that came in from the cold: Capital controls and the information content of order flow, Working Paper 2021/86, Central Bank of Iceland.

Brennan, M. J. & Cao, H. H. (1997), 'International portfolio investment flows', *The Journal of Finance* **52**(5), 1851–1880.

CGFS (2021), 'The changing pattern of capital flows', (66).

Choe, H., Kho, B.-C. & Stulz, R. M. (2005), 'Do domestic investors have an edge? the trading experience of foreign investors in korea', *The Review of Financial Studies* **18**(3), 795–829.

Danielsson, J. & Love, R. (2006), 'Feedback Trading', *International Journal of Finance and Economics* **11**, 35–53.

Danielsson, J. & Payne, R. (2002), 'Real Trading Patterns and Prices in Spot Foreign Exchange Markets', *Journal of International Money and Finance* **21**(2), 203–222.

Dvořák, T. (2005), 'Do domestic investors have an information advantage? evidence from indonesia', *The Journal of Finance* **60**(2), 817–839.

Ferreira, M. A., Matos, P., Pereira, J. P. & Pires, P. (2017), 'Do locals know better? a comparison of the performance of local and foreign institutional investors', *Journal of Banking and Finance* **82**, 151–164.

Froot, K. A., O'Connell, P. G. & Seasholes, M. S. (2001), 'The portfolio flows of international investors', *Journal of Financial Economics* **59**(2), 151–193.

Gompers, P. A. & Metrick, A. (2001), *The Quarterly Journal of Economics* **116**(1), 229–259.

Grinblatt, M. & Keloharju, M. (2000), 'The investment behavior and performance of various investor types: a study of finland's unique data set', *Journal of Financial Economics* **55**(1), 43–67.

Gyntelberg, J., Loretan, M. & Subhanij, T. (2012), Exchange rate fluctuations and international portfolio rebalancing in thailand. IMF Working Paper.

Gyntelberg, J., Loretan, M. & Subhanij, T. (2018), 'Private information, capital flows, and exchange rates', *Journal of International Money and Finance* **81**, 40–55.

Gyntelberg, J., Loretan, M., Subhanij, T. & Chan, E. (2014), 'Exchange rate fluctuations and international portfolio rebalancing', *Emerging Markets Review* **18**, 34–44.

Hau, H. & Rey, H. (2005), 'Exchange Rates, Equity Prices, and Capital Flows', *The Review of Financial Studies* **19**(1), 273–317.

Ho, E. H. C. (2022), 'Foreign participation in local currency government bond markets in emerging asia: Benefits and pitfalls to market stability', *Journal of International Money and Finance* **128**, 102699.

Hördahl, P. & Valente, G. (2022), Emerging market bond flows and exchange rate returns. BIS Working Paper 1042.

Kaniel, R., Liu, S., Saar, G. & Titman, S. (2012), 'Individual investor trading and return patterns around earnings announcements', *The Journal of Finance* **67**(2), 639–680.

Kim, W. & Wei, S.-J. (2002), 'Foreign portfolio investors before and during a crisis', *Journal of International Economics* (56), 77–96.

Koosakul, J. & Ananchotikul, N. (2019), Foreign exchange order flows and the thai exchange rate dynamics. Bank of Thailand Discussion Paper.

Koosakul, J. & Shim, I. (2021), 'The effects of asset price volatility on market participation: Evidence from the thai foreign exchange market', *Journal of Banking and Finance* **124**, 106036.

Lundblad, C. T., Shi, D., Zhang, X. & Zhang, Z. (2022), Are foreign investors informed? trading experiences of foreign investors in china.

Menkhoff, L., Sarno, L., Schmeling, M. & Schrimpf, A. (2012), 'Currency momentum strategies', *Journal of Financial Economics* **106**, 660–684.

Menkhoff, L., Sarno, L., Schmeling, M. & Schrimpf, A. (2016), 'Information flows in foreign exchange markets: Dissecting customer currency trades', *The Journal of Finance* **71**(2), 601–634.

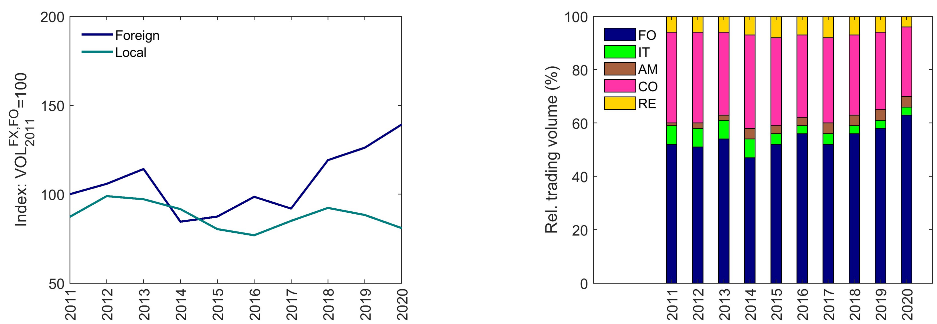
Richards, A. (2005), 'Big fish in small ponds: The trading behavior and price impact of foreign investors in asian emerging equity markets', *Journal of Financial and Quantitative Analysis* **40**(1), 1–27.

Figures

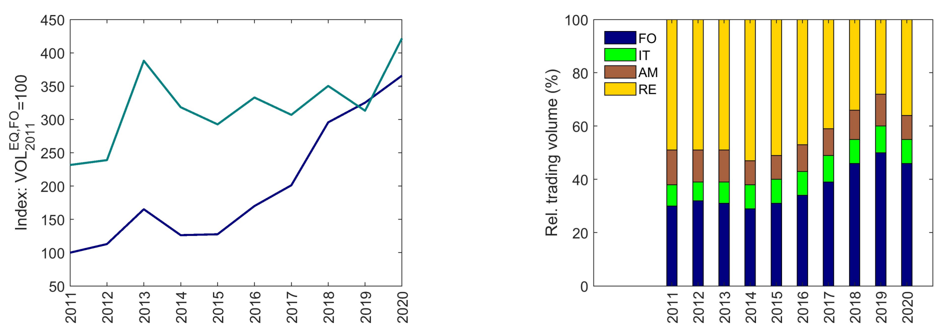
Figure 1: **Absolute and Relative Trading Volume: Foreign and Local Investors**

This figure shows time-series dynamics of normalized trading volumes of foreign investors and local market participants in foreign exchange ("FX", Panel A), equity ("EQ", Panel B), and long-term fixed income ("LD", Panel C) markets. The left column shows average yearly trading volume of foreign and local investors, where volumes of both investor groups are indexed by foreign trading volume in year 2011. The left column shows relative trading volumes of foreign investors and individual local market participants (in percentage). The sample period is January 2011 to August 2020.

(A) **Foreign Exchange**



(B) **Equity**



(C) **Long-term Debt**

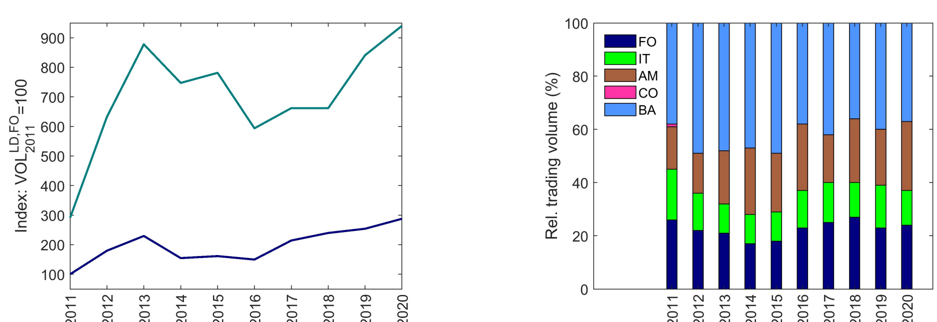
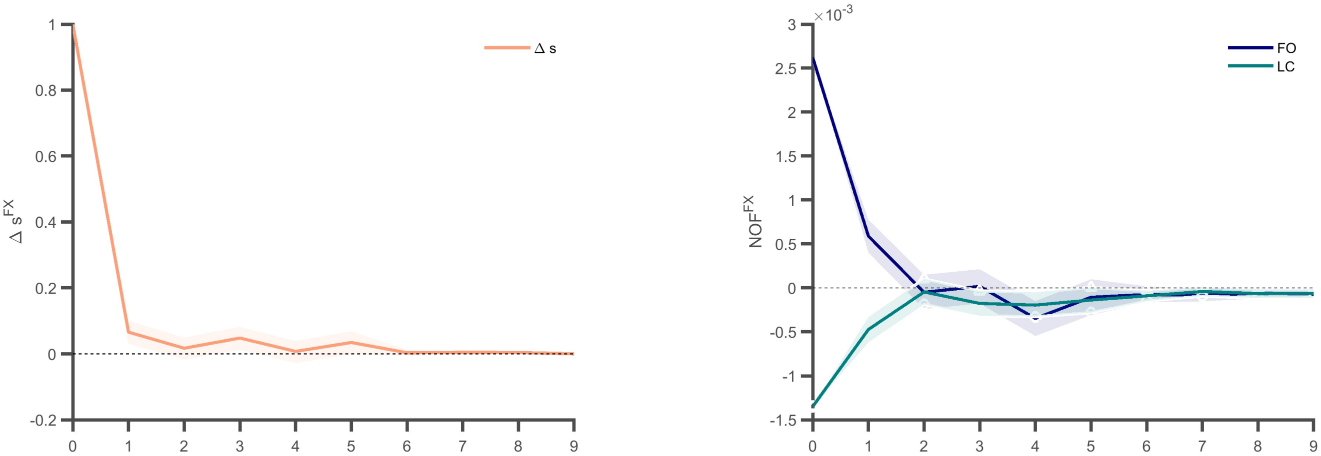


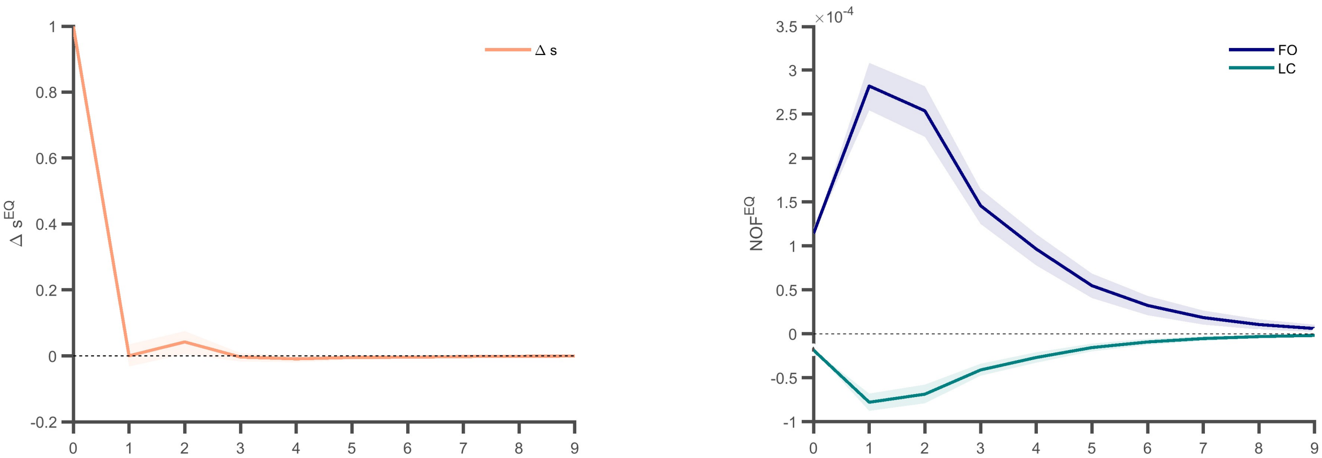
Figure 2: **Impulse Response Functions: Shock to Returns**

This figure shows impulse response functions (IRFs) of foreign ($NOF^{FC,c}$), and local ($NOF^{LC,c}$) normalized order flow to a one-unit shock in returns (Δs^c) in foreign exchange (top), equity (middle), and fixed income markets (bottom). The shaded areas refer 90% confidence intervals, the x-axis refers to the numbers of days subsequent to the innovation on day zero. Positive (Negative) order flow implies net buying (selling) pressure of local assets.

(A) $\Delta s^{FX} \rightarrow NOF^{FO}, NOF^{LC}$



(B) $\Delta s^{EQ} \rightarrow NOF^{FO}, NOF^{LC}$



(C) $\Delta s^{LD} \rightarrow NOF^{FO}, NOF^{LC}$

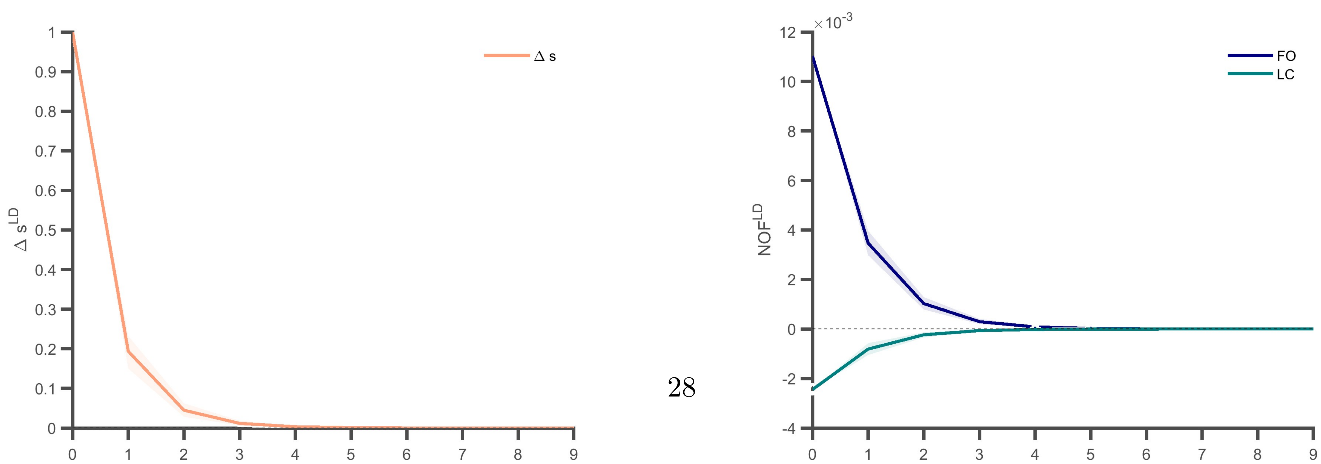
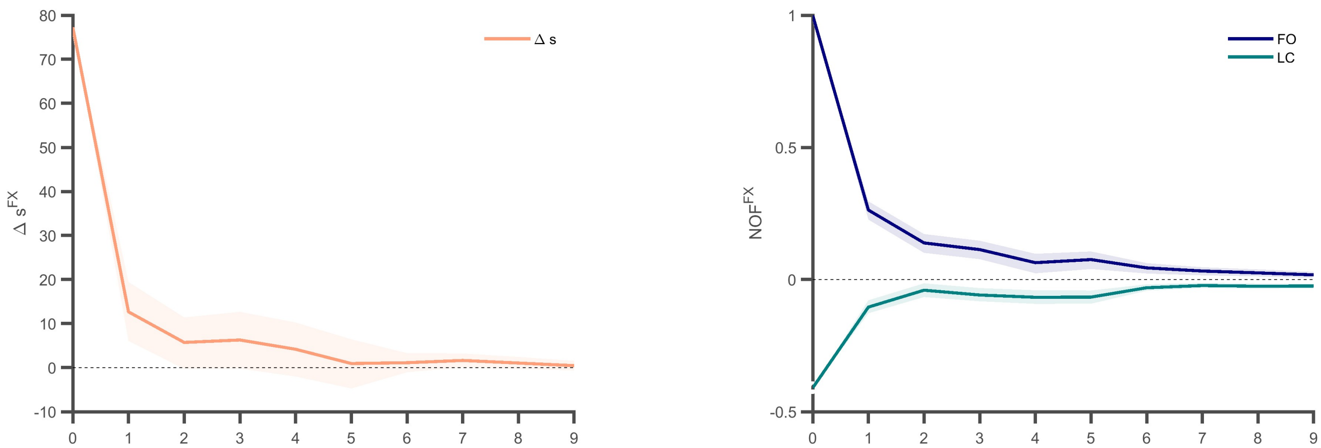


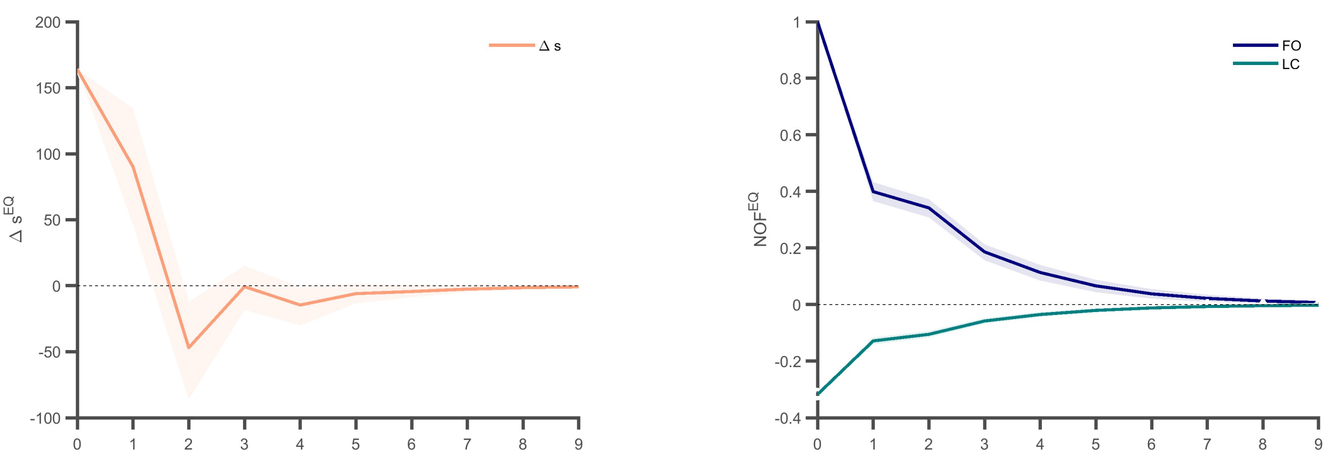
Figure 3: **Impulse Response Functions: Shock to Foreign Order Flow**

This figure shows impulse response functions (IRFs) of returns (Δs^c) and local normalized order flow ($NOF^{LC,c}$) to a one-unit shock in foreign normalized order flow ($NOF^{FO,c}$) in foreign exchange (top), equity (middle), and fixed income markets (bottom). The response of returns are measured in basis points. The shaded areas refer 90% confidence intervals, the x-axis refers to the numbers of days subsequent to the innovation on day zero. Positive (Negative) order flow implies net buying (selling) pressure of local assets.

(A) $NOF^{FO} \rightarrow \Delta s^{FX}, NOF^{LC}$



(B) $NOF^{FO} \rightarrow \Delta s^{EQ}, NOF^{LC}$



(C) $NOF^{FO} \rightarrow \Delta s^{LD}, NOF^{LC}$

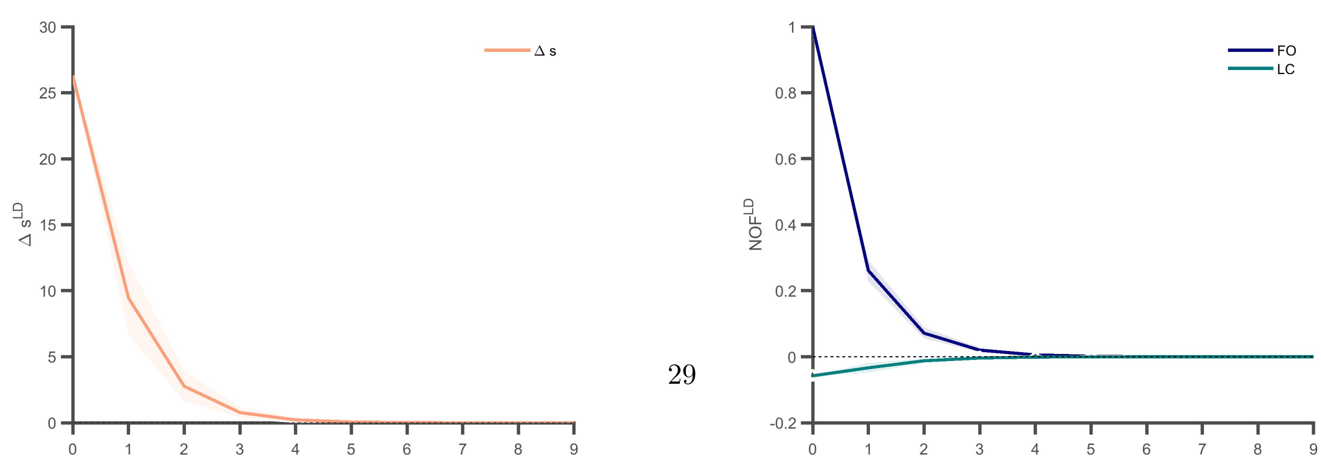
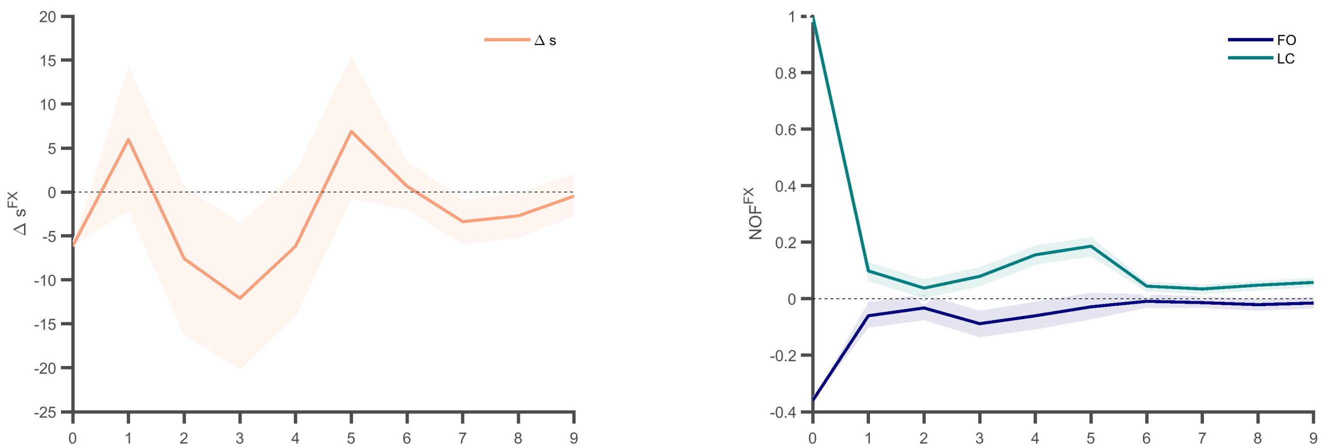


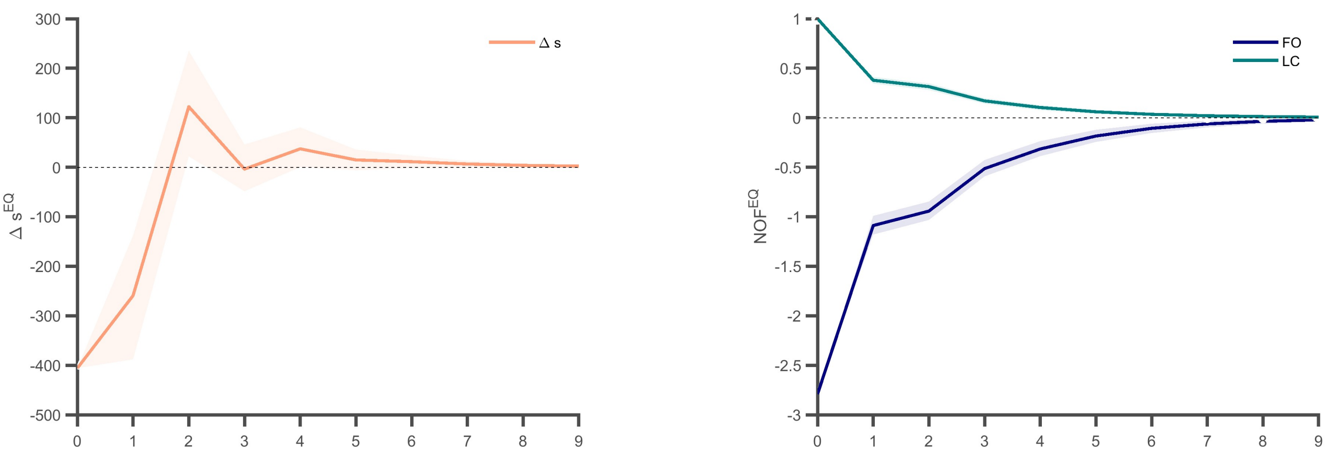
Figure 4: **Impulse Response Functions: Shock to Local Order Flow**

This figure shows impulse response functions (IRFs) of returns (Δs^c) and foreign normalized order flow ($NOF^{FO,c}$) to a one-unit shock in local normalized order flow ($NOF^{LC,c}$) in foreign exchange (top), equity (middle), and fixed income markets (bottom). The response of returns are measured in basis points. The shaded areas refer 90% confidence intervals, the x-axis refers to the numbers of days subsequent to the innovation on day zero. Positive (Negative) order flow implies net buying (selling) pressure of local assets.

(A) $NOF^{LC} \rightarrow \Delta s^{FX}, NOF^{FO}$



(B) $NOF^{LC} \rightarrow \Delta s^{EQ}, NOF^{FO}$



(C) $NOF^{LC} \rightarrow \Delta s^{LD}, NOF^{FO}$

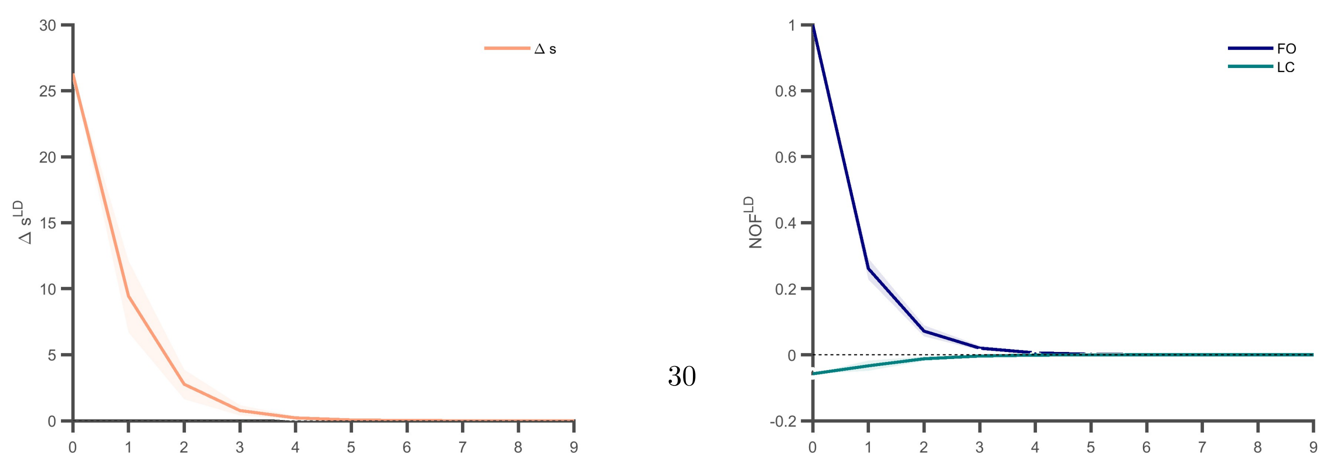


Figure 5: **Local investor trading and IRFs: Innovations to returns**

This figure shows impulse response functions of normalized order flow of local investor types to a one-unit shock in returns (Δs^c) in foreign exchange (top), equity (middle), and fixed income markets (bottom). The shaded areas refer 90% confidence intervals, the x-axis refers to the numbers of days subsequent to the innovation on day zero. Positive (Negative) order flow implies net buying (selling) pressure of local assets. The left column shows the responses of "financial" market participants, i.e., institutional investors (IT) and asset managers (AM), and local banks (BA). The right column shows the responses for corporates (CO), and retail investors (RE) (i.e., "non-financial" market participants).

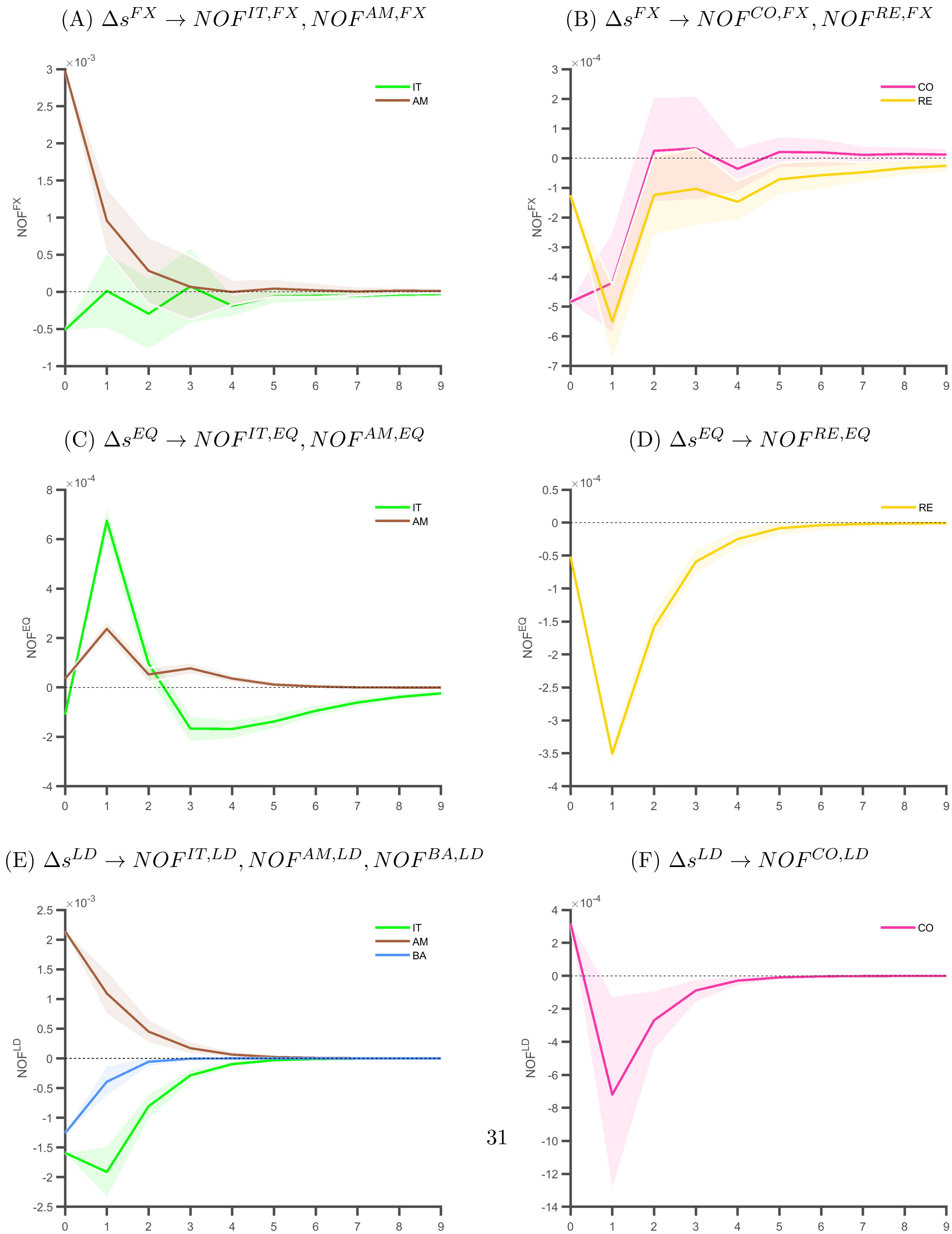
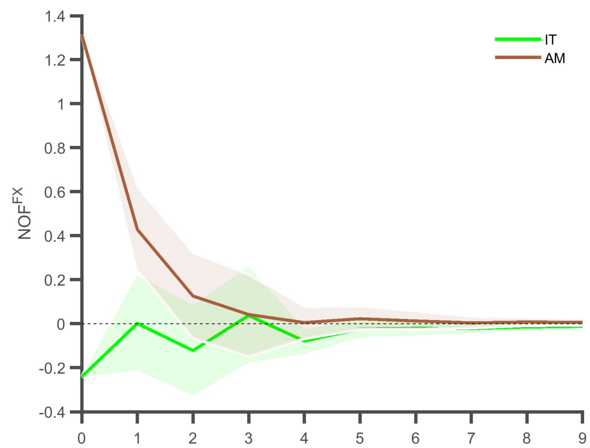


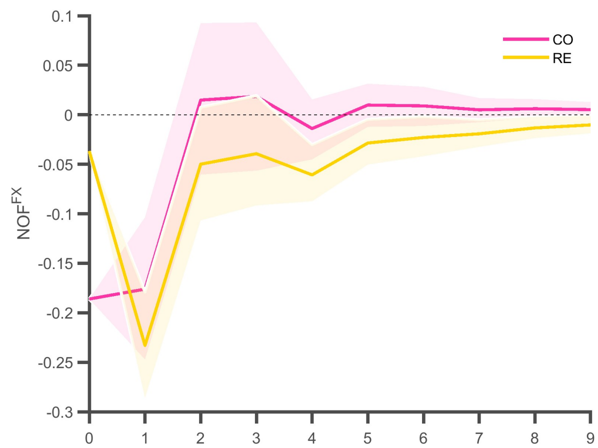
Figure 6: **Local investor trading and IRFs: Innovations to foreign investor order flow**

This figure shows impulse response functionsof normalized order flow from local investor types to a one-unit shock to foreign investor normalized order low (NOF^c) in the foreign exchange (FX), equity (EQ), or fixed income (LD) markets. The shaded areas refer 90% confidence intervals, the x-axis refers to the numbers of days subsequent to the innovation on day zero. Positive (Negative) order flow implies net buying (selling) pressure of local assets. The left column shows the responses of "financial" market participants, i.e., institutional investors (IT) and asset managers (AM), and local banks (BA). The right column shows the responses for corporates (CO), and retail investors (RE) (i.e., "non-financial" market participants).

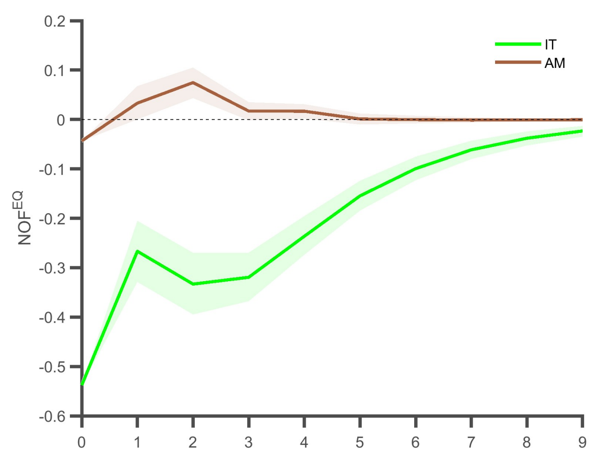
(A) $NOF^{FO,FX} \rightarrow NOF^{IT,FX}, NOF^{AM,FX}$



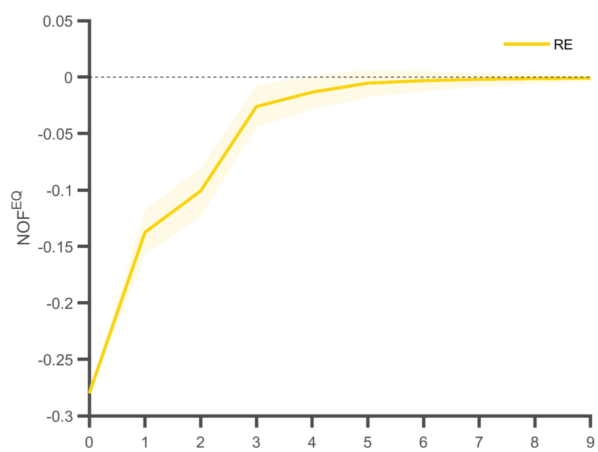
(B) $NOF^{FO,FX} \rightarrow NOF^{CO,FX}, NOF^{RE,FX}$



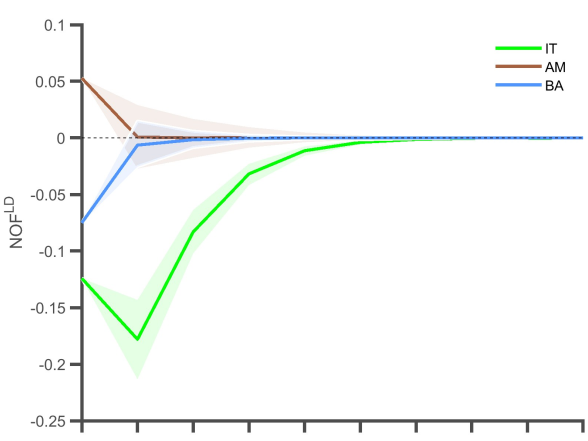
(C) $NOF^{FO,EQ} \rightarrow NOF^{IT,EQ}, NOF^{AM,EQ}$



(D) $NOF^{FO,EQ} \rightarrow NOF^{RE,EQ}$



(E) $NOF^{FO,LD} \rightarrow NOF^{IT,LD}, NOF^{AM,LD}, NOF^{BA,LD}$



(F) $NOF^{FO,LD} \rightarrow NOF^{CO,LD}$

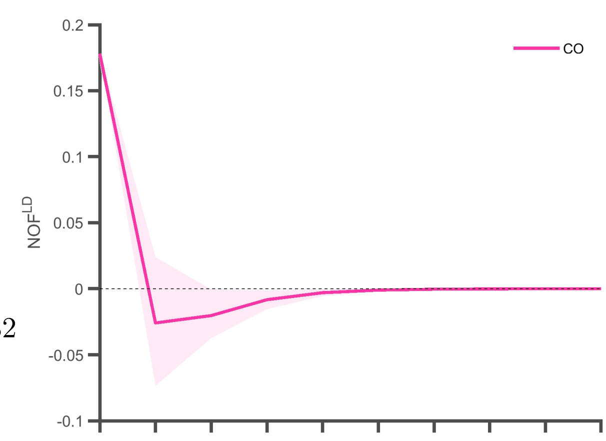


Figure 7: **News and Order Flow**

This figure shows the proportion of foreign (FO, navy) and local (LC, teal) order flow that is explained by news at different frequencies. For each asset class - foreign exchange (FX), equity (EQ), and fixed income (LD) - the adjusted $\bar{R}^2$ is reported for data sampled at the weekly (W), monthly (M), and quarterly (Q) frequency. The sample period is January 2011 to August 2020.

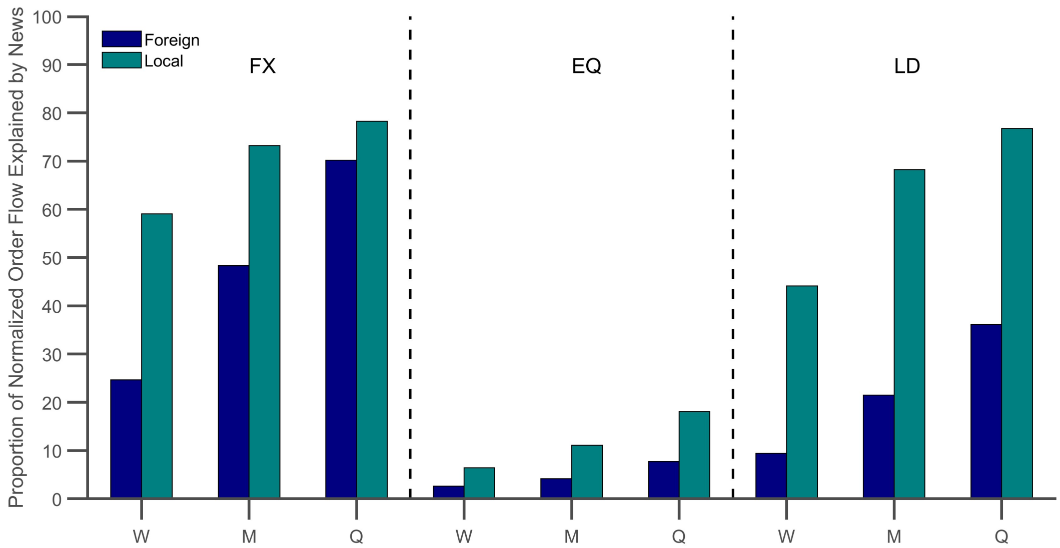
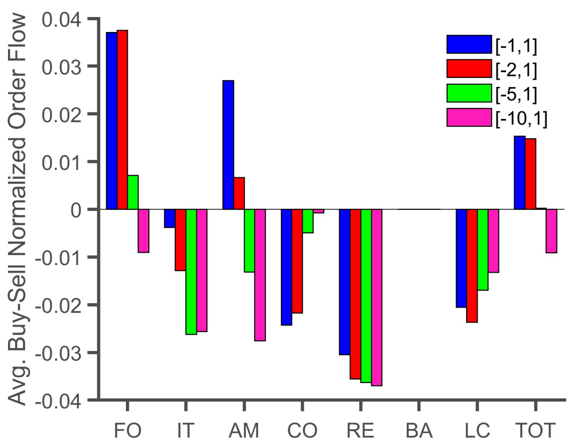


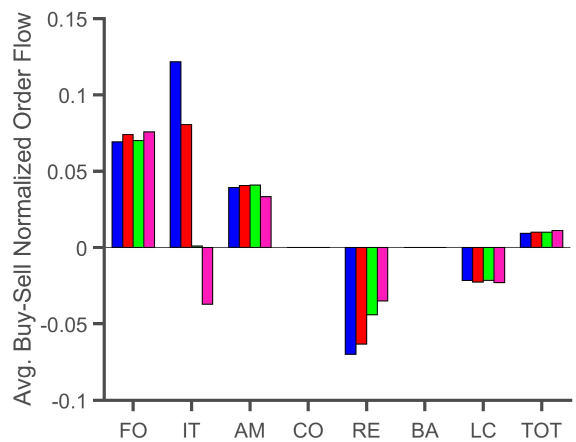
Figure 8: **Past Returns and Momentum Trading By Investor Group**

This figure shows the average difference between buy and sell order flow based on past returns over different formation periods. If past returns during a formation period are positive (negative), we assume an investor buys (sells) THB assets. The bars show the average difference in order flow between these long and short positions. Note: a positive difference is in line with momentum trading. We consider different formation periods from one day (i.e. -1) to 10 days (i.e.-10). The holding period is always one day, i.e., the portfolio is rebalanced on a daily basis. The x-axis refers to different investor types. The y-axis shows the average difference between long and short normalized order flow positions. The sample period is January 2011 to August 2020.

(A) **Foreign Exchange**



(B) **Equity**



(C) **Long-term Debt**

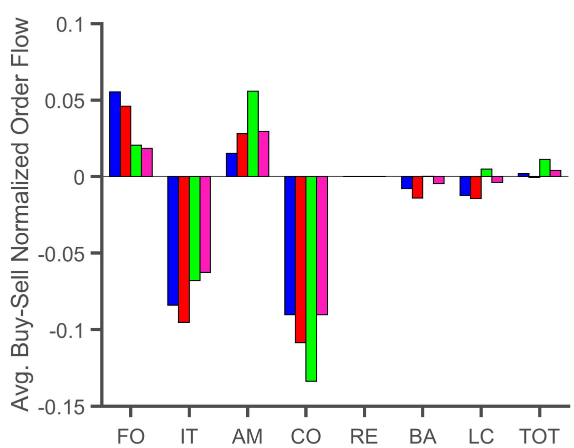
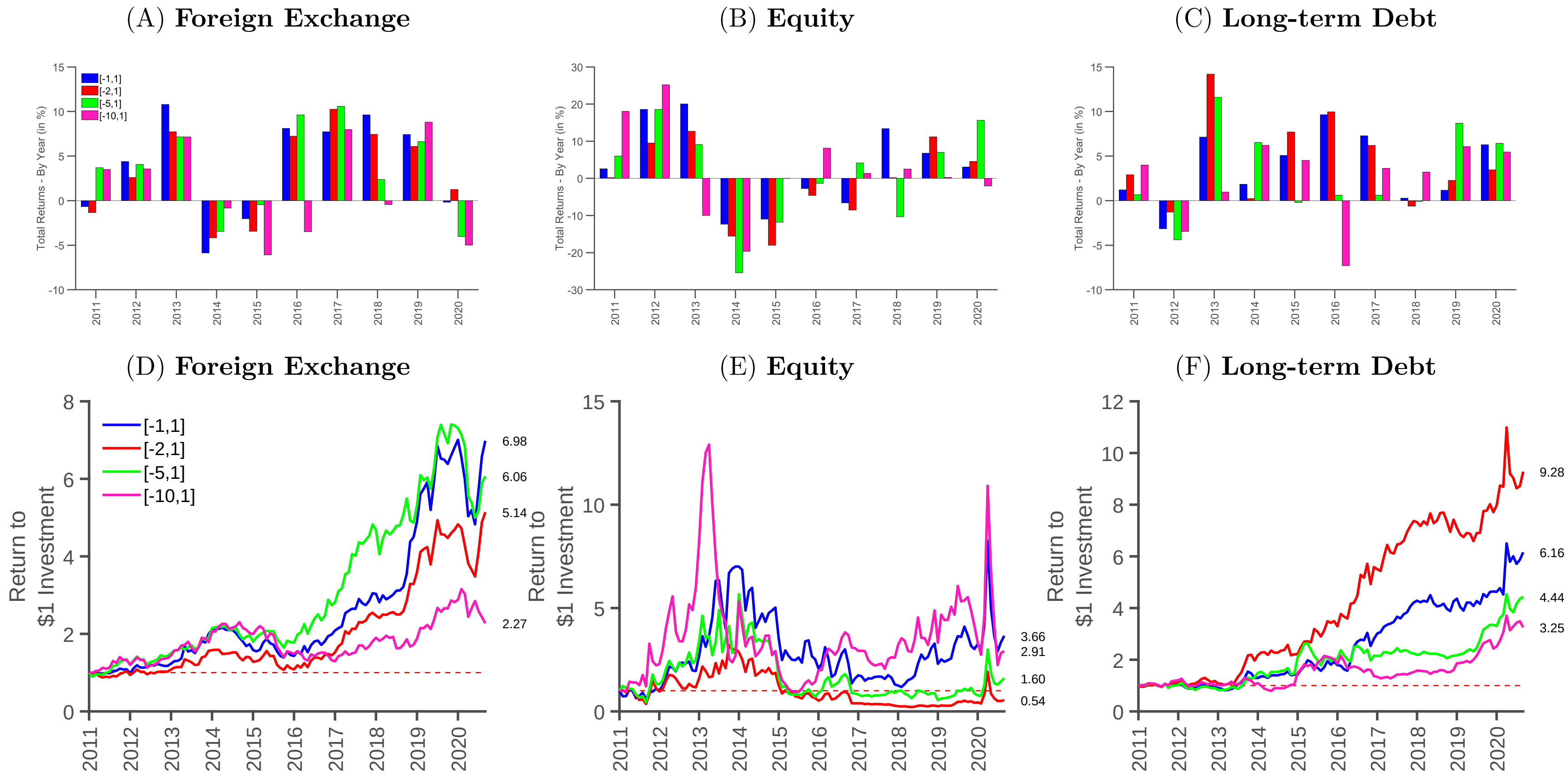


Figure 9: **Foreign Investor Momentum Trading and Profitability**

This figure shows the profitability of momentum trading of foreign investors. The top row shows total yearly returns of a momentum trading strategy in the foreign exchange (Panel A), equity (Panel B), and fixed income (Panel C) market. We consider different formation periods from one day (i.e. -1) to 10 days (i.e.-10). The holding period is always one day, i.e., the portfolio is rebalanced on a daily basis. The bottom panels (Panel D to E) show total monthly return indices, and the growth of a $1 investment in the beginning of the sample period. The sample period is January 2011 to August 2020.



Tables

Table 1

Summary Statistics

This table reports summary statistics of returns and daily normalized order flow across different asset classes: Foreign Exchange (Panel A), Equity (Panel B), and Fixed Income (Panel C) for different investor groups. Reported are the daily mean (median) and corresponding t-statistic (z-statistic) as well as standard deviation, skewness and kurtosis. Normalized order flow is defined as buyer- minus seller-initiated trading volume, divided by total daily trading volume. Normalized order flow ranges between -1 and 1, whereby a positive value implies larger buying than selling volumes of THB assets. Blank columns imply the respective investor group is not actively trading in the market segment. The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange									
	Δs	FO	IT	AM	CO	RE	BA	LC	TOT
Mean	-0.15	0.08	-0.30	-0.58	-0.06	0.15		-0.09	-0.01
t-stat	(-0.24)	(20.77)	(-35.86)	(-77.35)	(-17.95)	(63.50)		(-34.82)	(-2.69)
Median	0.00	0.08	-0.30	-0.68	-0.05	0.16		-0.09	-0.00
z-stat	(0.80)	(17.74)	(-28.99)	(-40.44)	(-15.39)	(40.61)		(-26.43)	(-1.34)
Std. Dev.	30.22	0.18	0.41	0.36	0.15	0.12		0.13	0.09
Skewness	0.09	-0.17	0.45	1.27	0.09	-0.42		0.03	-0.13
Kurtosis	5.74	3.09	2.87	4.43	3.28	5.33		3.15	3.40
ACorr	0.07	0.32	0.07	0.23	0.23	0.34		0.17	0.23
Panel B: Equity									
	Δs	FO	IT	AM	CO	RE	BA	LC	TOT
Mean	0.92	0.01	0.02	0.00		0.00		0.01	0.01
t-stat	(0.42)	(6.21)	(5.76)	(0.55)		(2.39)		(8.34)	(21.97)
Median	4.99	0.01	0.03	0.00		0.00		0.00	0.01
z-stat	(3.32)	(4.35)	(5.29)	(1.22)		(1.30)		(7.19)	(18.02)
Std. Dev.	105.57	0.10	0.19	0.08		0.06		0.03	0.01
Skewness	-1.21	0.32	-0.05	-0.16		-0.20		-0.29	0.29
Kurtosis	18.52	5.29	3.12	4.74		5.13		7.35	4.78
ACorr	-0.01	0.50	0.30	0.13		0.36		0.45	0.44
Panel C: Fixed Income									
	Δs	FO	IT	AM	CO	RE	BA	LC	TOT
Mean	0.92	0.08	0.21	0.12	0.16		0.02	0.09	0.09
t-stat	(1.33)	(8.80)	(24.63)	(17.10)	(13.93)		(4.76)	(24.15)	(25.87)
Median	0.27	0.09	0.23	0.14	0.00		0.02	0.09	0.09
z-stat	(3.08)	(7.68)	(19.49)	(14.85)	(12.62)		(2.88)	(19.75)	(21.19)
Std. Dev.	33.51	0.42	0.42	0.35	0.56		0.23	0.18	0.17
Skewness	-0.06	-0.13	-0.36	-0.33	0.03		0.12	0.00	-0.04
Kurtosis	22.68	2.48	2.72	2.95	2.82		3.82	3.20	3.20
ACorr	0.14	0.25	0.27	0.34	0.07		0.06	0.16	0.12

Table 2

VAR Estimation and Instruments

The table provides information on the types of instruments that are employed in the VAR estimation for Foreign Exchange (Panel A), Equity (Panel B), and Long-term Debt (Panel C) markets. The column "2.Stage" refers to the left-hand side variable in the second-stage regressions, "1.Stage" refers to the endogeneous variables in the first-stage regression, and "Instruments" lists the variables used as instruments. Panel D provides diagnostic statistics from the instrumental variable regressions. $p - val^{Instr.1}$ and $p - val^{Instr.1}$ show the p-value of an F-test of excluded instruments. The row "J-stat" refers to the p-value of the Hansen J-statistics (i.e., a test of overidentifying restrictions with the null hypothesis that the instruments are valid.), and "End." reports the p-value of endogeneity tests (i.e., a test with the null hypothesis that the specified endogeneous regressors can be treated as exogeneous). The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange

2.Stage	1.Stage	Instruments
Δs^{FX}	$\text{NOF}^{FO,FX}$; $\text{NOF}^{LC,FX}$	$\text{CDS}_{t-1:t-7}$; $\Delta s^{THBEUR}_{t:t-3}$; $\text{RR}^{1W}_{t-1:t-2}$; $\text{NOF}^{EQ,LC}_{t-1:t-3}$; $\text{NOF}^{EQ,FO}_{t-1:t-3}$; $\text{NOF}^{LD,LC}_{t-1:t-3}$; $\text{NOF}^{LD,FO}_{t-1:t-3}$; $\text{NOF}^{FX,FO}_{t-6:t-10}$; $\text{NOF}^{FX,LC}_{t-6:t-10}$; $\Delta s^{FX}_{t-6:t-10}$
$\text{NOF}^{FO,FX}$	$\text{NOF}^{LC,FX}$; Δs^{FX}	$\text{CDS}_{t-1:t-7}$; $\Delta s^{THBEUR}_{t:t-3}$; $\text{RR}^{1W}_{t-1:t-2}$; $\text{NOF}^{EQ,LC}_{t-1:t-3}$; $\text{NOF}^{EQ,FO}_{t-1:t-3}$; $\text{NOF}^{LD,LC}_{t-1:t-3}$; $\text{NOF}^{LD,FO}_{t-1:t-3}$; $\text{NOF}^{FX,FO}_{t-6:t-10}$; $\text{NOF}^{FX,LC}_{t-6:t-10}$; $\Delta s^{FX}_{t-6:t-10}$;
$\text{NOF}^{LC,FX}$	$\text{NOF}^{FO,FX}$; Δs^{FX}	Δs^{JPY}_{t-1}, Δs^{SGD}_{t-1}, Δs^{MYR}_{t-1}, Δs^{KRW}_{t-1}, RR^{1W}_{t-1},$\text{NOF}^{EQ,FO}_{t-1:t-3}$

Panel B: Equity

2.Stage	1.Stage	Instruments
Δs^{EQ}	$\text{NOF}^{FO,EQ}$; $\text{NOF}^{LC,EQ}$	$\text{CDS}_{t-1:t-5}$; $\Delta s^{EW}_{t:t-3}$; $\text{NOF}^{FX,FO}_{t-1:t-3}$; $\text{NOF}^{FX,LC}_{t-1:t-3}$; $\text{NOF}^{LD,FO}_{t-1:t-3}$; $\text{NOF}^{LD,LC}_{t-1:t-3}$
$\text{NOF}^{FO,EQ}$	$\text{NOF}^{LC,EQ}$; Δs^{EQ}	$\text{CDS}_{t-1:t-5}$; $\Delta s^{JP}_{t-1:t-2}$; Δs^{SG}_{t-1}
$\text{NOF}^{LC,EQ}$	$\text{NOF}^{FO,EQ}$; Δs^{EQ}	$\text{CDS}_{t-1:t-5}$; $\Delta s^{JP}_{t-1:t-2}$; Δs^{SG}_{t-1}

Panel C: Fixed Income

2.Stage	1.Stage	Instruments
Δs^{LD}	$\text{NOF}^{FO,LD}$; $\text{NOF}^{LC,LD}$	$\text{CDS}_{t-1:t-10}$; $\Delta s^{FX}_{t-1:t-2}$; $\Delta s^{EQ}_{t-1:t-2}$; $RR^{FX}_{t-1:t-2}$;$\Delta s^{EW}_{t-1:t-2}$; $\text{NOF}^{FX,FO}_{t-1:t-3}$; $\text{NOF}^{FX,LC}_{t-1:t-3}$; $\text{NOF}^{EQ,FO}_{t-1:t-3}$; $\text{NOF}^{EQ,LC}_{t-1:t-3}$
$\text{NOF}^{FO,LD}$	Δs^{LD}; $\text{NOF}^{LC,LD}$	$\text{CDS}_{t-1:t-10}$;$\Delta s^{JP}_{t-1:t-5}$; $\text{NOF}^{FX,FO}_{t-1:t-2}$; $\text{NOF}^{FX,LC}_{t-1:t-2}$; $\text{NOF}^{EQ,FO}_{t-1:t-2}$; $\text{NOF}^{LD,LC}_{t-1:t-2}$
$\text{NOF}^{LC,LD}$	Δs^{LD}; $\text{NOF}^{FO,LD}$	$\text{CDS}_{t-1:t-10}$; $\Delta s^{FX}_{t-1:t-2}$; $\Delta s^{EQ}_{t-1:t-2}$; $RR^{FX}_{t-1:t-2}$;$\Delta s^{asia}_{t-1:t-2}$; $\text{NOF}^{FX,FO}_{t-1:t-3}$; $\text{NOF}^{FX,LC}_{t-1:t-3}$; $\text{NOF}^{EQ,FO}_{t-1:t-3}$; $\text{NOF}^{LD,LC}_{t-1:t-3}$

Panel D: IV-Regression Diagnostics

	FX			EQ			LD		
	Δs	NOF^{FO}	NOF^{LC}	Δs	NOF^{FO}	NOF^{LC}	Δs	NOF^{FO}	NOF^{LC}
$\text{p-val}^{Instr.1}$	0.00	0.00	0.00	0.00	0.20	0.20	0.00	0.01	0.06
$\text{p-val}^{Instr.2}$	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.19	0.00
J-stat	0.05	0.10	0.09	0.53	0.39	0.20	0.38	0.32	0.19
End.	0.29	0.98	0.10	0.76	0.10	0.15	0.99	0.13	0.27

Table 3

VAR Estimation

The table reports the contemporaneous regression coefficients from the IV-VAR estimation (Panel A) and regression diagnostics of the instrumental variable regressions (Panel B) for each of the three asset classes. The columns Δs^c, $NOF^{FO,c}$, and $NOF^{LC,c}$ refer to returns, foreign order flow, and local order flow in asset class c, with $c \in \{FX, EQ, LD\}$, indicate data from the foreign exchange, equity, and long-term debt markets, respectively. In Panel A, the row "p" refers to the number of lags used in the VAR regression, determined by the Bayes Information Criterion. The row "p-val" refers to the p-value of a F-test that right-hand side regressors are jointly zero. The sample period is January 2011 to August 2020.

	FX			EQ			LD		
	Δs	NOF^{FO}	NOF^{LC}	Δs	NOF^{FO}	NOF^{LC}	Δs	NOF^{FO}	NOF^{LC}
Δ s		0.00	0.00		0.00	0.00		0.01	0.01
		(4.42)	(-0.81)		(0.72)	(0.63)		(2.21)	-1.37
NOF^{FO}	87.72			307.94		-0.32	27.25		0.01
	(4.40)			(0.61)		(-6.45)	(1.70)		(0.12)
NOF^{LC}	25.47	-0.35	-0.38	453.61	-2.77		16.31	-1.02	
	(1.33)	(-3.45)	(-3.11)	(0.32)	(-6.74)		(0.48)	(-1.38)	

Table 4

Persistent Impact of Foreign Investor Order Flow

The table reports the estimated coefficients of the following predictive regression

$$\sum \Delta s^{c}_{t+1:t+h} = \alpha + \beta NOF^{c,i}_{t} + \varepsilon_{t+1:t+h}$$

where $\sum \Delta s^{c}_{t+1:t+h}$ refers to the cumulative returns of the period t+1:t+h days ahead in asset class c and $NOF^{c,i}_{t}$ refers to normalized order flow in asset class c of either foreign or local investors. The forecasting horizon varies between 1-Day and 1-Month. Numbers in parentheses refer to t-statistics, based on Newey-West adjusted standard errors. All variables have been normalized to allow for a comparison across asset classes. For brevity the estimate of the intercept is omitted. Panel A, B, and C report results for the foreign exchange, equity, and fixed income markets. The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange					
	1Day	2-Day	1-Week	2-Week	1-Month
Foreign Investors					
NOF	0.08	0.08	0.07	0.05	0.03
	(3.74)	(2.95)	(2.69)	(1.57)	(0.95)
$\bar{R}^2$	0.01	0.01	0.00	0.00	0.00
Local Investors					
NOF	0.00	-0.03	-0.04	-0.03	-0.02
	(0.12)	(-1.15)	(-1.74)	(-1.11)	(-0.55)
$\bar{R}^2$	0.00	0.00	0.00	0.00	0.00
Panel B: Equity					
	1Day	2-Day	1-Week	2-Week	1-Month
Foreign Investors					
NOF	0.05	0.01	0.01	0.04	0.01
	(2.41)	(0.36)	(0.15)	(1.21)	(0.26)
$\bar{R}^2$	0.00	0.00	0.00	0.00	0.00
Local Investors					
NOF	-0.05	-0.02	-0.03	-0.06	-0.03
	(-2.43)	(-0.68)	(-0.92)	(-1.65)	(-0.62)
$\bar{R}^2$	0.00	0.00	0.00	0.00	0.00
Panel C: Fixed Income					
	1Day	2-Day	1-Week	2-Week	1-Month
Foreign Investors					
NOF	0.10	0.09	0.04	0.02	0.01
	(3.98)	(3.49)	(1.47)	(0.52)	(0.25)
$\bar{R}^2$	0.01	0.01	0.00	0.00	0.00
Local Investors					
NOF	0.00	0.00	0.02	0.00	-0.02
	(-0.18)	(-0.21)	(0.93)	(0.09)	(-0.72)
$\bar{R}^2$	0.00	0.00	0.00	0.00	0.00

Table 5

Foreign Investors and Portfolio Rebalancing

This table reports regression results associated with foreign investory portfolio rebalancing activity. The left (right) hand panel focuses on the link between foreign investor trading in equity (long term fixed income) markets and the implications for foreign exchange markets. Variables refer to daily returns of the Thai baht (r_t^{FX}) or foreign investor trading dynamics in the equity ($\mathrm{NOF}_t^{EQ,FO}$) or long-term fixed income ($\mathrm{NOF}_t^{LD,FO}$) market, or the return spread between local and U.S. equity ($r_t^{TH,EQ} - r_t^{US,EQ}$) and bond $r_t^{TH,LD} - r_t^{US,LD}$ markets. Foreign investor foreign exchange trading (NOF_t^{FX}), daily VIX (VIX_t) and the slope of the U.S. yield curve are included as additional control variables ($\mathrm{10M3M}_t$). The sample period is January 2011 to August 2020.

Panel A: Contemporaneous Regressions						
	Equity			Fixed Income		
	r_t^{FX}	$\mathrm{NOF}_t^{EQ,FO}$	r_t^{FX}	r_t^{FX}	$\mathrm{NOF}_t^{LD,FO}$	r_t^{FX}
α	-1.23	0.05***	1.45	-1.13	0.22***	15.40***
	(-0.40)	(3.95)	(0.46)	(-0.39)	(3.65)	(3.54)
$\mathrm{NOF}_t^{EQ,FO}$	37.10***					
	(5.40)					
$r_t^{TH,EQ} - r_t^{US,EQ}$		0.00***	0.01			
		(4.55)	(1.50)			
$\mathrm{NOF}_t^{LD,FO}$				9.32***		
				(6.38)		
$r_t^{TH,LD} - r_t^{US,LD}$					0.00***	0.07***
					(3.12)	(5.55)
NOF_t^{FX}	73.13***	0.09***	76.27***	76.15***	0.03	76.30***
	(18.83)	(6.70)	(19.51)	(19.85)	(0.52)	(19.80)
VIX_t	-0.10	-0.00***	-0.18	-0.13	-0.01***	-0.35**
	(-0.59)	(-4.62)	(-1.14)	(-0.82)	(-2.82)	(-2.34)
$\mathrm{10M3M}_t$	-2.04***	0.01**	-1.58**	-2.08***	0.05***	0.30
	(-2.74)	(2.27)	(-2.05)	(-2.78)	(3.42)	(0.35)
Obs	2,356	2,356	2,356	2,356	2,356	2,356
$\bar{R}^2$	0.22	0.06	0.20	0.22	0.02	0.22

Table 6

Persistent vs. Transitory Order Flow

The table reports the estimated coefficients of the following predictive regression

$$\Delta s_{t+1}^{c} = \alpha + \beta^{P} PNOF_{t}^{c,i} + \beta^{T} TNOF_{t}^{c,i} + \varepsilon_{t+1}$$

where Δs_{t+1}^{c} refers to the returns during period t+1 in asset class c. $PNOF_{t}^{c,i}$ and $TNOF_{t}^{c,i}$ refer to the permanent and transitory component of normalized order flow in asset class c of either foreign or local investors. The permanent component is defined as the moving average over the previus 1-, 3- or 6-months, and the transitory component is the difference between observed normalized order flow and the permanent component. Numbers in parentheses refer to t-statistics, based on Newey-West adjusted standard errors. All variables have been normalized to allow for a comparison across asset classes. For brevity the estimate of the intercept is omitted. The sample period is January 2011 to August 2020.

	Foreign			Local		
	FX	EQ	LD	FX	EQ	LD
Mov. Avg.: 1-Month						
$PNOF$	0.03	0.01	0.01	-0.01	-0.01	-0.02
	(1.30)	(0.45)	(0.46)	(-0.58)	(-0.55)	(-0.72)
$TNOF$	0.08	0.06	0.10	0.00	-0.06	0.00
	(3.63)	(2.94)	(4.30)	(0.08)	(-2.75)	(0.03)
$\bar{R}^2$	0.01	0.00	0.01	0.00	0.00	0.00
Mov. Avg.: 3-Months						
$PNOF$	0.03	0.01	0.00	0.02	-0.01	0.00
	(1.48)	(0.41)	(0.09)	(0.73)	(-0.30)	(0.11)
$TNOF$	0.08	0.06	0.10	0.01	-0.05	0.00
	(3.57)	(2.95)	(4.25)	(0.33)	(-2.60)	(0.21)
$\bar{R}^2$	0.01	0.00	0.01	0.00	0.00	0.00
Mov. Avg.: 6-Months						
$PNOF$	0.01	0.01	-0.01	0.03	0.00	-0.01
	(0.39)	(0.49)	(-0.44)	(1.04)	(-0.01)	(-0.31)
$TPNOF$	0.08	0.06	0.09	0.00	-0.06	0.00
	(3.40)	(2.96)	(4.00)	(0.02)	(-2.68)	(0.25)
$\bar{R}^2$	0.01	0.00	0.01	0.00	0.00	0.00

Appendix

AE.1 Institutional Background

Non-resident investor market access. Non-resident investors that hold bank balances in Thailand are required to do so by holding so-called non resident baht accounts (NRBAs). Foreign currencies converted into baht are normally (though not necessarily) deposited in NRBAs before being invested in equities and bond securities, and correspondingly the proceeds of sales of equities and bonds by non-residents are deposited first in NRBAs before being converted into foreign currencies.

If non-resident investors in Thailand wish to build up their positions in long-term baht denominated financial assets such as bonds or equities, they can do so in the short run only in the following three ways: (i) by drawing down their existing baht-denominated bank balances held in NRBAs; (ii) via trading shorter-term fixed income assets (including money market claims) with domestic market participants, or (iii) by engaging in baht-denominated FX transactions.

Because of the limits on allowable balances in NRBAs and because of a general lack of liquidity in the private money markets in Thailand, non-resident investors normally acquire the funds involved in the purchase of baht-denominated equities and bonds by transacting in the FX market. Due to this institutional feature it is possible to link foreign investor trading across FX, equities, and long-term bonds in Thai financial markets.

The local foreign exchange market. The wholesale onshore FX market in Thailand is an over-the-counter market, where trading services are provided by licensed currency dealers, which can be domestic or foreign-owned banks and brokers.

The onshore FX market in Thailand is closely monitored by the Bank of Thailand (BoT). Onshore commercial banks are required by the BoT to limit their net FX positions in any one currency. Dealers usually manage to adhere to these limits by conducting transactions in the FX swaps markets. The position limits tend to be particularly important for the branches of foreign banks that operate in Thailand. All licensed FX dealers submit detailed daily reports of their FX transactions to the BoT. For each transaction banks report the counterparty, its type (other dealer, domestic customer, non-resident customer, and BOT), the volume (in dollar equivalent), the currencies involved (by far the majority of all transactions are in Thai baht vs. U.S. dollars), the applicable exchange rate, and the type of transaction.

AE.2 Additional Tables

Table A-I

Average Relative Trading Volume: By Year and Investor Type

This table provides information on the average relative trading volume by year and investor type. The different types of investors include foreign investors (FO) and the following local investor groups: institutional investors (IT), asset managers (AM), corporates (CO), retail investors (RE), and banks (BA). The sum of domestic investors is denoted as LC (local). The sum of FO and LC equal 1. Blank rows mean the respective investor group is not actively trading in the market segment. The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange										
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FO	0.52	0.51	0.54	0.47	0.52	0.55	0.52	0.56	0.58	0.63
IT	0.07	0.07	0.07	0.07	0.04	0.03	0.04	0.03	0.03	0.03
AM	0.01	0.02	0.02	0.04	0.03	0.03	0.04	0.04	0.04	0.04
CO	0.34	0.34	0.31	0.35	0.33	0.31	0.32	0.30	0.29	0.26
RE	0.06	0.06	0.06	0.07	0.08	0.07	0.08	0.07	0.06	0.05
BA										
LC	0.48	0.49	0.46	0.53	0.48	0.45	0.48	0.44	0.42	0.37
Panel B: Equity										
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FO	0.30	0.32	0.31	0.29	0.31	0.33	0.39	0.46	0.50	0.46
IT	0.08	0.07	0.08	0.09	0.09	0.09	0.10	0.09	0.10	0.09
AM	0.13	0.12	0.12	0.09	0.09	0.10	0.10	0.11	0.12	0.09
CO										
RE	0.49	0.49	0.49	0.53	0.51	0.47	0.41	0.34	0.28	0.36
BA										
LC	0.70	0.68	0.69	0.71	0.69	0.67	0.61	0.54	0.50	0.54
Panel C: Fixed Income										
	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FO	0.26	0.22	0.21	0.17	0.17	0.22	0.25	0.27	0.23	0.24
IT	0.19	0.14	0.11	0.11	0.11	0.14	0.15	0.13	0.16	0.13
AM	0.16	0.15	0.20	0.25	0.22	0.25	0.18	0.24	0.21	0.26
CO	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RE										
BA	0.38	0.49	0.48	0.47	0.49	0.38	0.42	0.36	0.40	0.37
LC	0.74	0.78	0.79	0.83	0.83	0.78	0.75	0.73	0.77	0.76

Table A-II

Predictive Regressions: Disaggregated Local Order Flow

The table reports the estimated coefficients of the following predictive regression

$$\sum \Delta s^{c}_{t+1:t+h} = \alpha + \beta OF^{c,i}_{t} + \varepsilon_{t+h}$$

where $\sum \Delta s^{c}_{t+h}$ refers to the cumulative returns of the period t+1:t+h days ahead in asset class c and $NOF^{c,i}_{t}$ refers to normalized order flow in asset class c of different local market participants. The forecasting horizon varies between 1-Day and 1-Month. Numbers in parentheses refer to t-statistics, based on Newey-West adjusted standard errors. All variables have been normalized to allow for a comparison across asset classes. For brevity the estimate of the intercept is omitted. Panel A, B, and C report results for the foreign exchange, equity, and fixed income markets. The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange					
	1-Day	2-Day	1-Week	2-Week	1-Month
β^{IT}	0.00	0.01	0.02	-0.02	-0.03
	(0.19)	(0.33)	(0.72)	(-1.01)	(-1.49)
β^{AM}	0.01	0.01	-0.01	0.01	0.00
	(0.55)	(0.41)	(-0.26)	(0.29)	(0.02)
β^{CO}	-0.01	-0.03	-0.04	-0.02	-0.01
	(-0.42)	(-1.30)	(-1.27)	(-0.65)	(-0.31)
β^{RE}	-0.01	-0.02	-0.04	-0.01	-0.02
	(-0.66)	(-1.05)	(-1.36)	(-0.25)	(-0.44)
Panel B: Equity					
	1-Day	2-Day	1-Week	2-Week	1-Month
β^{IT}	-0.01	0.00	-0.02	-0.01	0.02
	(-0.28)	(-0.10)	(-0.95)	(-0.22)	(0.81)
β^{AM}	-0.01	0.00	-0.03	-0.02	-0.02
	(-0.68)	(0.10)	(-1.29)	(-0.71)	(-1.14)
β^{RE}	-0.03	-0.02	-0.01	-0.04	-0.03
	(-1.60)	(-0.63)	(-0.36)	(-1.42)	(-0.98)
Panel C: Fixed Income					
	1-Day	2-Day	1-Week	2-Week	1-Month
β^{IT}	0.00	0.00	0.02	0.00	0.01
	(-0.26)	(-0.12)	(0.82)	(0.06)	(0.20)
β^{AM}	0.04	0.02	-0.01	-0.04	-0.07
	(2.09)	(0.90)	(-0.32)	(-1.23)	(-1.98)
β^{CO}	-0.03	0.00	0.00	0.02	0.02
	(-1.46)	(0.09)	(-0.19)	(0.76)	(0.82)
β^{BA}	-0.04	-0.02	0.01	-0.01	-0.01
	(-1.69)	(-0.79)	(0.40)	(-0.29)	(-0.45)

Table A-III

Foreign Investors and Portfolio Rebalancing (Lagged Regressors)

This table reports regression results associated with foreign investory portfolio rebalancing activity. The left (right) hand panel focuses on the link between foreign investor trading in equity (long term fixed income) markets and the implications for foreign exchange markets. Variables refer to daily returns of the Thai baht (r_t^{FX}) or foreign investor trading dynamics in the equity ($\mathrm{NOF}_t^{EQ,FO}$) or long-term fixed income ($\mathrm{NOF}_t^{LD,FO}$) market, or the return spread between local and U.S. equity ($r_t^{TH,EQ} - r_t^{US,EQ}$) and bond $r_t^{TH,LD} - r_t^{US,LD}$ markets. Foreign investor foreign exchange trading (NOF_{t-1}^{FX}), daily VIX (VIX_{t-1}) and the slope of the U.S. yield curve are included as additional control variables ($\mathrm{10M3M}_{t-1}$). All explanatory variables enter the regressions with a lag. The sample period is January 2011 to August 2020.

	Equity			Fixed Income		
	r_t^{FX}	$\mathrm{NOF}_t^{EQ,FO}$	r_t^{FX}	r_t^{FX}	$\mathrm{NOF}_t^{LD,FO}$	r_t^{FX}
α	3.15	0.08***	21.89***	3.50	0.16***	7.78*
	(1.15)	(6.12)	(7.95)	(1.30)	(2.64)	(1.90)
NOF_{t-1}^{EQ}	20.47***					
	(3.05)					
$r_{t-1}^{TH,EQ} - r_{t-1}^{US,EQ}$		0.00***	0.08***			
		(8.11)	(12.46)			
NOF_{t-1}^{LD}				2.07		
				(1.46)		
$r_{t-1}^{TH,LD} - r_{t-1}^{US,LD}$					0.00*	0.02
					(1.77)	(1.53)
NOF_{t-1}^{FX}	11.85***	0.07***	12.04***	13.60***	0.16***	13.63***
	(3.20)	(6.16)	(3.24)	(3.66)	(2.89)	(3.67)
VIX_{t-1}	-0.10	-0.00***	-0.31***	-0.13	-0.01**	-0.19
	(-0.68)	(-4.99)	(-2.63)	(-0.90)	(-2.54)	(-1.24)
$\mathrm{10M3M}_{t-1}$	-1.71**	0.01***	0.63	-1.64**	0.04***	-1.03
	(-2.37)	(3.23)	(0.79)	(-2.21)	(2.82)	(-1.21)
Obs	2,355	2,355	2,355	2,355	2,355	2,355
$\bar{R}^2$	0.01	0.13	0.11	0.01	0.02	0.01

Table A-IV

Foreign Investor Momentum Trading Returns: Summary Statistics

This table reports summary statistics of foreign investor momentum returns across different asset classes - Foreign Exchange (Panel A), Equity (Panel B), and Fixed Income (Panel C). We consider different formation periods from one day (i.e. -1) to 10 days (i.e.-10). The holding period is always one day, i.e., the portfolio is rebalanced on a daily basis. Reported are monthly mean and corresponding t-statistics as well as standard deviation, skewness and kurtosis, and autocorrelation. The sample period is January 2011 to August 2020.

Panel A: Foreign Exchange				
	[-1,1]	[-2,1]	[-5,1]	[-10,1]
Mean	4.07	3.48	3.74	1.57
t-stat	(2.56)	(2.28)	(2.49)	(0.97)
Std. Dev.	17.09	16.47	16.20	17.33
Skewness	0.26	0.23	-0.45	-0.54
Kurtosis	3.39	3.20	3.77	3.50
ACorr	0.04	0.07	-0.02	-0.02
Panel B: Equity				
	[-1,1]	[-2,1]	[-5,1]	[-10,1]
Mean	3.28	-0.87	1.20	2.45
t-stat	(0.68)	(-0.15)	(0.21)	(0.43)
Std. Dev.	51.89	61.42	61.20	61.88
Skewness	0.04	0.55	0.56	0.83
Kurtosis	3.88	6.37	5.50	6.10
ACorr	-0.01	0.00	-0.04	0.01
Panel C: Fixed Income				
	[-1,1]	[-2,1]	[-5,1]	[-10,1]
Mean	3.80	4.66	3.15	2.41
t-stat	(2.17)	(2.81)	(1.71)	(1.33)
Std. Dev.	18.85	17.84	19.81	19.52
Skewness	1.11	0.20	0.57	0.45
Kurtosis	7.17	3.94	5.25	5.19
ACorr	-0.05	-0.13	-0.00	0.05