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The beneficial aspect of FX volatility for market liquidity[1]

Jakree Koosakul[2] and Ilhyock Shim[3]

Abstract

A substantial body of existing research suggests that asset price volatility is harmful to market liquidity. This paper explores a contrarian view that, by creating opportunities for profit making, exchange rate volatility can be beneficial to trading activity. Utilising granular data from the Thai foreign exchange (FX) market from January 2010 to March 2016, we find that the volatility of the US dollar–Thai baht exchange rate has significant positive effects on trading volume in the spot market, except at very high levels of volatility. We also observe significant heterogeneity in such effects across different types of market participant. In particular, FX volatility has positive effects on the FX trading activity of foreign and interbank players, but it negatively affects that of local players. These results are robust when we control for potential confounding variables, such as information arrivals, that can generate a positive but non-causal co-movement between volatility and volume.

JEL classification: F31, G12.

Keywords: asset price volatility, foreign exchange market, investor type, market liquidity, nonlinear effect.

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1 Introduction

The financial crisis of 2007–09 and the subsequent bouts of financial market turbulence generated renewed interest in the relationship between asset price volatility and market liquidity. With respect to the effect of the former on the latter, a substantial body of existing research suggests that asset price volatility reduces market liquidity. From a market making perspective, inventory models in the spirit of Demsetz (1968), Stoll (1978) and Ho and Stoll (1981) suggest that increased asset price volatility, which implies increased liquidation risk, may disincentivise market makers from providing their intermediation services. From an end-investor perspective, Pagano (1989) shows that high market volatility can keep prospective investors out of the market, which in turn generates an endogenous loop of market thinness and high volatility. More recently, Brunnermeier and Pedersen (2009) highlight an important linkage between funding liquidity and market liquidity, whereby heightened market volatility can create a vicious cycle of tightening funding liquidity and deteriorating market liquidity.

This paper takes a different stance to these studies. In particular, it explores the notion that a reasonable level of market volatility can be beneficial to market liquidity. The intuition is that without adequate market volatility, return-motivated market participants may feel less inclined to remain active due to the existence of transaction costs and the perceived lack of profit-making opportunities. There are very few papers in the literature that explicitly consider this beneficial aspect of market volatility. Herrera (2005) builds a theoretical model of endogenous market participation and shows that in the presence of entry cost – most naturally interpreted as the cost of information acquisition needed to be informed in a particular asset market – traders may have little incentive to enter the market unless it is sufficiently volatile. Jeanne and Rose (2002) also model entry cost, and consider an equilibrium in which the benefit of entry is increasing with FX volatility.

We keep the theoretical motivations offered by Herrera (2005) and Jeanne and Rose (2002) in the background and take an empirical approach to examining the issue. To this end, we utilise a granular transaction-level dataset of spot trading in the Thai foreign exchange (FX) market to conduct regression analyses on the determinants of market trading liquidity, with a particular focus on the role of market volatility, in both normal and turbulent periods. Among various FX market liquidity measures, we focus on trading volume in the spot FX market.

The main results of the paper are the following. First, when we run our baseline regression of weekly aggregate market trading volume on FX volatility and other covariates, we find that the effect of volatility on trading volume is positive and significant. This finding is robust when we control for potential confounding variables, especially information-related factors, as well as when we use alternative measures of trading liquidity and volatility. We also check if these baseline results are subject to potential bias due to reverse causality.[4] Overall evidence suggests that FX volatility

[4] An analysis of splitting volatility into the expected and unexpected components suggests that information arrival does not affect volatility and trading volume at the same time. However, this does not necessarily establish the direction of causality from volatility to trading volume. Nevertheless, the potential bias arising from reverse causality (ie market liquidity affecting volatility) is likely to be negative. Therefore, reverse causality should not be responsible for the observed positive coefficient. Also, the results of a VAR analysis reported in Appendix 2 and the regressions including lagged volatility lend additional support for the direction of causality from volatility to market liquidity.

has a positive causal effect on market liquidity, in line with the theoretical prediction offered by Herrera (2005) and Jeanne and Rose (2002).

Second, an additional regression analysis suggests there is significant nonlinearity in the volatility–liquidity relationship. Specifically, while the effect of volatility on liquidity is positive on average, at very high levels of volatility such positive influence diminishes greatly. This result is important since it implies that our baseline finding on the beneficial aspect of market volatility does not lead to a rejection of the more vicious aspects of market volatility in the previous studies, such as Pagano (1989) and Brunnermeier and Pedersen (2009). More specifically, we show that when the market is sufficiently calm, a small dose of price fluctuations is likely to improve market liquidity by encouraging traders to become more active; beyond a certain threshold of volatility, however, the "fear factor" aspects appear to start kicking in and volatility becomes more hurtful than helpful.

Third, while the aggregate effect of market volatility is positive overall, participant-level regression results highlight significant heterogeneity with regards to participants' response to volatility. Specifically, while volatility has a positive impact on the trading activity of foreign and interbank players, it negatively affects the activity of local players. This is consistent with the notion that only return-motivated participants feel encouraged to participate more actively, following an increase in asset price movements. Local investors in Thailand are mainly real-sector businesses engaged in the FX market primarily to facilitate their international trade/business operations. It is possible that these players wish to trade less in the spot market as the exchange rate becomes volatile, relying instead on the derivatives market to reduce their FX exposure. This finding is important since it highlights that even at reasonable levels of market volatility, volatility is liquidity-enhancing only in certain market segments, while liquidity-damaging in others. In other words, market volatility affects not only the total level of market participation, but also the *composition* of market players active in the market.

Last, in addition to market volatility, variations in the Thai FX spot market trading activity can be explained by several other factors, namely domestic and global funding conditions, market makers' risk appetite, the risk perception of global investors, and information arrivals in the market. Significant asymmetry of liquidity in up and down markets also appears to be present. These findings confirm a number of results found in previous studies on the drivers of market liquidity. Interestingly, however, we also find that the significance of these factors also depends on the choice of liquidity measures used, as well as on the type of market participant being examined. Specifically, trading volume and frequency tend to vary significantly to changes in market conditions. Trading size, on the other hand, appears to be little affected. We interpret this finding as reflecting the fact that trading size may be a product of longer-term structural features of the market, such as conventional market practices and traders' trading limits. On participant-level heterogeneity, as with the result on the effect of market volatility, local investors are the least responsive to changes in market conditions, both domestic and global, while interbank players are the most sensitive.

The rest of the paper is organised as follows. Section 2 provides literature review. Section 3 explains the empirical methodologies and key variables. Section 4 describes data and Section 5 presents the empirical results. Section 6 investigates endogeneity and nonlinear effects, and also conducts robustness checks. Finally, Section 7 concludes.

2 Literature review

This paper's contributions to the existing literature are threefold. First and foremost, it contributes to the debate on the effects of market volatility. From a real-sector perspective, there is a large literature examining the negative aspects of market volatility. Obstfeld and Rogoff (1998), for instance, theoretically show that exchange rate volatility leads to lower economic welfare, by creating fluctuations in domestic income from international trade, which in turn lead to consumption fluctuations, and by causing higher price levels as firms attach an exchange rate risk premium to the price of their products. While the results from the empirical literature have been rather mixed, several studies have also shown that for developing countries where derivatives markets may not be well developed, exchange rate volatility appears to have a statistically significant negative impact on growth and trade performance (see, for instance, Aghion et al (2009) and Grier and Smallwood (2007)).

As discussed in the previous section, the negative aspects of market volatility in relation to financial markets' liquidity have also been widely explored. This paper aims to contribute to the literature by exploring a potential positive effect of market volatility on market liquidity, thereby adding weight to the other side of the argument. In doing so, we also explore a potential nonlinear effect of market volatility. That is, we examine the possibility that volatility is beneficial to market liquidity up to a certain level, after which the negative effects of market volatility explored by the earlier papers start kicking in.

Second, we aim to make a contribution to the literature by shedding more light on the mechanisms behind the positive volatility–volume relationship documented in a number of market microstructure studies. To be sure, our hypothesis is not the only channel that explains a positive relationship between volatility and trading volume. In fact, there exists a substantial body of research documenting a positive volatility–volume relationship, mostly for stock markets where data were traditionally more accessible. Karpoff (1987) provides a review of the earlier literature, while Canarella and Pollard (2011) and Carroll and Kearney (2015) give an overview of more recent studies. For FX markets, Galati (2001), Bauwens et al (2005) and Rime and Sucarrat (2007) are examples of such studies. In these papers, however, there is no direct causal link between market volatility and trading volume. Instead, Clark (1973)'s pioneering work on the mixture of distribution hypothesis suggests that volatility and volume co-move simply because they are simultaneously determined by a common, unobservable factor, namely arrivals of new information in the market. In this paper, we attempt to separate this confounding "information arrival" effect from the more causal effect that market volatility may have on market liquidity.

Third, we also contribute to a strand of literature on the drivers of market liquidity. Research in this area is also extensive, dating back to such studies as Demsetz (1968), Benston and Hagerman (1974) and Stoll (1978), which examine the cross-sectional determinants of the bid–ask spread in the US stock market. More recently, Chordia et al (2001) provide a comprehensive study on the time-series determinants of market liquidity. Using data on trading activity in addition to the bid–ask spread, they document the following stylised facts on the drivers of US stock market liquidity: (1) liquidity drops significantly in down markets; (2) liquidity materially moves in response to market volatility; and (3) liquidity displays strong day-of-the-week effects. For the FX market, a recent study by Karnaukh et al (2015) also provides an equally comprehensive study. Covering 40 currency markets, they find that variations in FX liquidity can be largely explained by two sets of factors, namely market conditions and the willingness of market makers to make markets.

While comprehensive, the majority of these studies have mainly focused on the drivers of aggregate liquidity.[5] To the extent that our granular data allow us to distinguish between the trading activity of different market participants – namely local, foreign and interbank players – we can examine the role of participant-level heterogeneity in the determination of aggregate liquidity. This question is especially interesting given the segmented structure of the FX market, and the diversity of its participants, which make it unclear whether the aggregate results obtained in the previous studies also hold at a more granular level.

3 Empirical methodology

This section discusses our empirical methodology, elaborates further on the concepts of market liquidity and market volatility, and provides a brief review of the standard determinants of market liquidity thus far explored in the literature.

To examine the role of market volatility in the determination of market liquidity, our baseline empirical methodology involves running a multiple linear regression of the following form:

$$liquidity_t = \beta_0 + \beta_1\, volatility_t + \boldsymbol{X_t \delta} + \epsilon_t \tag{1}$$

where $liquidity_t$ and $volatility_t$ are measures of aggregate trading liquidity and market volatility, respectively, and $\boldsymbol{X_t}$ is a vector containing other potential determinants of market liquidity. Several previous papers on market liquidity (for example, Chordia et al (2001), Chordia et al (2003) and Bjonnes et al (2003)) conduct their empirical analyses in daily frequency. In this paper, we conduct the estimation in lower frequency than daily to better capture the longer-term, and potentially less noise-driven, relationship between market liquidity and its determinants. Specifically, even though our trading volume data are available on a daily frequency basis, we estimate Equation (1) in weekly frequency.[6]

Before describing the data in Section 4, in the remainder of this section we provide a brief discussion of each of the three variables in Equation (1), including an elaboration of our liquidity and volatility measures, as well as our motivation for each of the control variables included in $\boldsymbol{X_t}$.

[5] To be sure, there already exist several papers examining the role of investor-level heterogeneity in market liquidity. For example, Bjonne et al (2003) find that the spot market volume of large banks is especially important in influencing market volatility. Similarly, Daigler and Wiley (1999) document that trades by "speculators" – traders located outside the actual market – tend to be more correlated with volatility than those by investors in the market. Nevertheless, to the best of our knowledge, there has been no study that explores investor-level heterogeneity in the context of examining the drivers of market liquidity.

[6] As a robustness check, we also conduct the regression analyses in this paper in daily frequency, and find that the qualitative conclusions reached are insensitive to the choice of time-series frequency. The results from these analyses are not reported but available upon request.

3.1 Market liquidity

Conceptually, a market is considered liquid if participants in the market are able to buy or sell an asset of interest with little execution cost in terms of both monetary expense and time. This attribute is commonly perceived as desirable since it promotes allocation and information efficiency in the market. A liquid financial market also ensures a smooth transmission of central bank policy implemented through market-based instruments.

Notwithstanding the general conceptual agreement, in practice there remains no consensus on how best to measure the different aspects of market liquidity.[7] Market liquidity has multiple dimensions and cannot be sufficiently described by a single measure. For example, Committee on the Global Financial System (2016) reports an ambiguous assessment of fixed-income market liquidity after the financial crisis of 2007–09, which reflects the difficulties in measuring market liquidity.[8]

Due to data availability issue, the bid–ask spread was commonly used in the earlier literatures (see, for example, Benston and Hagerman (1974) and Wei (1991)). The spread is a convenient and conceptually sound measure since it directly captures the *cost* of executing a small trade in the market.

As more data have become available, trading activity – measured by volume, frequency and size – has also gained popularity as a useful metric of market *breadth*. The key idea is that in a market of numerous and large trades, the orders of individual players should have little impact on the price of the asset since there are numerous uncorrelated demands ready to absorb such orders.

Beyond these relatively straightforward measures, other more rigorous metrics have also been proposed to capture more subtle aspects of market liquidity. For example, the market-impact measure, which quantifies the price impact of a standard-sized transaction, is a useful measure of how *resilient* the market is to liquidity shocks.

In this paper, we rely mainly on trading activity metrics as a measure of market trading liquidity. Specifically, we rely on trading volume data in estimating our main results, and also use alternative measures, namely trading frequency and size, in robustness checks. While the bid–ask spread is useful in other contexts, we cannot use the bid–ask spread to examine the role of participant-level heterogeneity in the determination of market liquidity, which is one of this paper's main objectives.[9]

7 A useful review of the different metrics that are commonly used to measure market liquidity is provided by Sarr and Lybek (2002).

8 Markets Committee (2017) also documents that during the sterling flash event on 7 October 2016, trading volume was higher than usual, the bid-ask spread was wider than its usual overnight average and the ratio between price move and trading volume was higher than the usual overnight level.

9 We also conduct a similar analysis using data on the USDTHB bid-ask spread. However, in contrast with a number of previous studies, we find that most factors in our model are not statistically significant in explaining the spread, with the exception of a proxy variable for the dealers' willingness to provide liquidity, which is significant in explaining spread and has the expected negative sign. This result may merit further investigation. However, in addition to not allowing us to analyse the drivers of participant-level liquidity, the use of bid-ask spread also has another important drawback. Specifically, as pointed out by Fleming (2003), the bid-ask spread simply captures the trading cost of executing a small-sized trade and in certain periods of time, and hence may not be an appropriate measure of market-wide liquidity. For these reasons, we do not explore the use of the bid-ask spread further in this paper.

By contrast, it is possible to use the market-impact metrics in a participant-specific way, by estimating a regression of price changes on participant-specific order flows. However, given that we need the time series of a particular market liquidity measure in our empirical analysis, it is not feasible to use market-impact metrics in our study.

3.2 Market volatility

Perhaps the simplest measure of asset price variability is period volatility. This can be measured by calculating the absolute or squared change in the asset price from the beginning to the end of a specified period. While convenient, an important drawback of this measure is that it does not capture movements of the asset price that may occur within the period. In view of this drawback, our main analyses rely instead on a measure of within-period volatility. Specifically, we use a high–low volatility measure, which captures the range within which the US dollar–Thai baht exchange rate (henceforth, USDTHB) moves within a given week.

In the robustness check section (Section 6), we also explore three alternative measures of market volatility. The first is within-week standard deviation of USDTHB, which should ideally capture similar information content to that reflected in the baseline high–low measure. The second is volatility obtained from the exponentially-weighted moving average (EWMA) procedure, which is intended to capture longer-term trends in the volatility of the exchange rate. Finally, we also explore volatility implied from USDTHB options, with a view that this may better capture the forward-looking elements of future uncertainty than other historical volatility measures. The time series of the different volatility measures are shown in Graph A in Appendix 1.[10]

3.3 Other drivers of market liquidity

The inclusion of other potential determinants of market volatility serves two major purposes. First, the inclusion allows us to study not only the effect of market volatility on market liquidity, but also the influence of other factors. In doing so, we are able to examine the drivers of participant-level market liquidity, which has been little explored so far.

Second and perhaps more importantly, the inclusion reduces the possibility of omitted variable bias in the estimated coefficient on market volatility. This bias can arise from several sources. Most notably, following the pioneering work by Clark (1973), there is a general agreement that trading volume and volatility tend to co-move positively because they are both affected by new information. Without controlling for this effect, the estimated coefficient on volatility is likely to be biased upward. Alternatively, it is also possible that both market volatility and trading activity are affected (negatively and positively, respectively) by market makers' willingness to provide liquidity. Without modelling such willingness, a downward bias in the coefficient may arise.

Our choice of variables to be included in vector $\boldsymbol{X_t}$ is mainly guided by previous studies in the area. The first set of variables relate to market conditions. Specifically, in addition to market volatility, market returns have also been identified as an

[10] The pairwise correlation coefficients of the different volatility measures are between 0.3 and 0.6. They suggest that, while sufficiently correlated, the different measures may not necessarily convey the same information on the degree of market turbulence at all times.

important determinant of market liquidity. Reasoning that liquidity providers are more likely to hit their capital constraints in down markets, Hameed et al (2010) find significant drops in market liquidity when stock market returns are negative. Chordia et al (2001) also find a similar pattern of asymmetry. Their explanation is that market makers may find it more difficult to adjust inventory in falling markets.

Second, considering that market participants' opportunity cost of trading should be significantly affected by the prevailing interest rates, we also include interest rate variables in $\boldsymbol{X}_t$. Our prior is that accommodative monetary conditions, by reducing the opportunity cost of trading, should induce higher trading activity in the financial markets. The influence of domestic monetary policy on market liquidity has already been explored by Goyenko and Ukhov (2009) for the stock and bond markets, and by Karnaukh et al (2013) for the FX market. In this paper, considering the increasingly global nature of modern financial markets, we examine the influence of not only domestic monetary conditions, but also global monetary conditions.

Third, we also consider measures of global investors' risk sentiment. All else equal, an improvement in global risk appetite should translate into an increase in trading activity in the riskier segments of the financial markets, especially those in emerging market economies. Several previous studies have found empirical support for this notion. Mancini et al (2013), for instance, find that FX liquidity is significantly driven by the VIX index, a popular measure of global risk aversion. Karnaukh et al (2013) also find similar evidence, albeit only in some specifications.[11]

Fourth, several theoretical models highlight an important linkage between participants' funding constraints and market liquidity. Brunnermeier and Pedersen (2009), for instance, show that the ability of traders to provide market liquidity is ultimately constrained by their ability to access funding. In a related model of "liquidity black holes", Morris and Shin (2004) show that market liquidity may be impaired following a sudden drop in asset prices, which causes traders to hit their loss limit and liquidate their positions. This in turn reduces two-sided market liquidity and generates further drops in asset prices. Guided by these models, our regression specifications also include a measure of market makers' funding availability.

Fifth, several papers show that there are significant seasonal patterns in the time-series evolution of market liquidity (see, for example, Chordia et al (2001)). We also explore some of these patterns in our empirical analysis.

Last and most importantly, when we examine the impact of market volatility on liquidity, it is crucial that we control for information arrivals in the market. In the baseline specifications, we tackle this issue by including a measure of stock and bond market volatilities in our regressions. Our identification strategy is that any arrival of new, unexpected information that potentially simultaneously drives both FX volatility and FX trading volume should also be reflected in stock and bond market volatilities. By including these two variables, a positive coefficient on FX market volatility should provide evidence supporting the notion that FX volatility has a causal positive effect on market liquidity. In addition to this admittedly simple strategy, we further address potentially remaining endogeneity problems in Section 6.

11 In other markets, Bao et al (2008) show that changes in aggregate corporate bond liquidity are strongly related to changes in the VIX index.

4 Data

For our measures of market trading liquidity, we utilise daily data on the Thai FX spot market we obtained from the Bank of Thailand (BOT). The BOT requires that all licenced FX dealing banks submit a detailed daily report of all FX transactions that they have conducted with their customers. The report includes details of each individual transaction, including information on, among others, the name of the counterparty, its type (other dealer, local customer or foreign customer), the transaction amount, the currencies involved, the exchange rate at the time of transaction, and the type of FX transaction.

Using the data, we construct three weekly aggregate measures of trading liquidity in the spot market, namely trading volume, frequency and size. Volume is obtained simply by adding the amount of all spot transactions that take place within a particular week, then dividing it by the number of trading days of that week. The division ensures that the weeks with more trading days do not, by construction, have higher volume than those with fewer days. Frequency is constructed in the same manner, only that the summation is now on the number of transactions instead of the amount. Size is calculated by dividing volume by frequency, which gives a measure of the average transaction size.

To examine the drivers of market trading liquidity at a more granular level, we also construct measures of participant-specific trading liquidity. In Thailand, as with other FX markets, FX transactions take place on an over-the-counter (OTC) basis. Under this setting, licenced bank dealers act as wholesale FX product providers to local and foreign end-customers. To manage their inventory positions from trading with these customers, those dealers in turn trade among themselves in the interbank segment of the market, which also constitutes a significant portion of the entire market trading activity. We distinguish between these three types of market player – namely, local end-customers, foreign end-customers and interbank players – when measuring participant-level liquidity. As with our aggregate metrics, we also measure disaggregate liquidity in terms of volume, frequency and size.

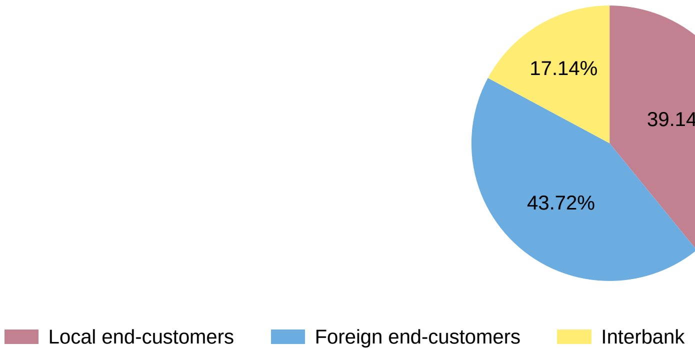
As an overview of the relative importance of the three investor types in the Thai FX spot market, Graph 1 shows the share of their trading volume. We find that dealer banks' trades with end-customers make up the majority of market trading volume, with local and foreign entities accounting for roughly the same share of the end-customer trades. The interbank segment, nevertheless, also constitutes a significant portion, accounting for around 17% of total activity.

From the BOT data, we are also able to directly see the main purposes for which different types of player trade in the Thai FX spot market.[12] As shown in Graph 2, there are indeed fundamental differences in the objectives under which the three types of player participate in the market. Local end-customers, who are mainly real-sector businesses, transact primarily for current account related purposes to facilitate their international trade operations. Foreign investors, on the other hand, participate mainly for investment purposes. A further examination of the data indicates that such investments are mainly portfolio investments. Although not clear from the graph,

[12] There are, admittedly, other private participants in the market, namely registered dealers other than commercial banks. However, the BOT data show that their trading activities represent a negligible portion. Therefore, we do not include those private participants in our empirical analysis.

interbank activities are mainly undertaken for the purpose of managing the inventory positions of market-making banks. Given the different purposes of trading, we view that our disaggregation of investor type is granular enough to capture important heterogeneity in the volatility–liquidity relationship in the Thai FX market.

Share of Thai FX spot market trading volume by key market players — Graph 1



The graph only covers trading activity of the three key types of private participant in the market. The sample period is from 4 January 2010 to 18 March 2016.

Sources: Bank of Thailand; authors' calculations.

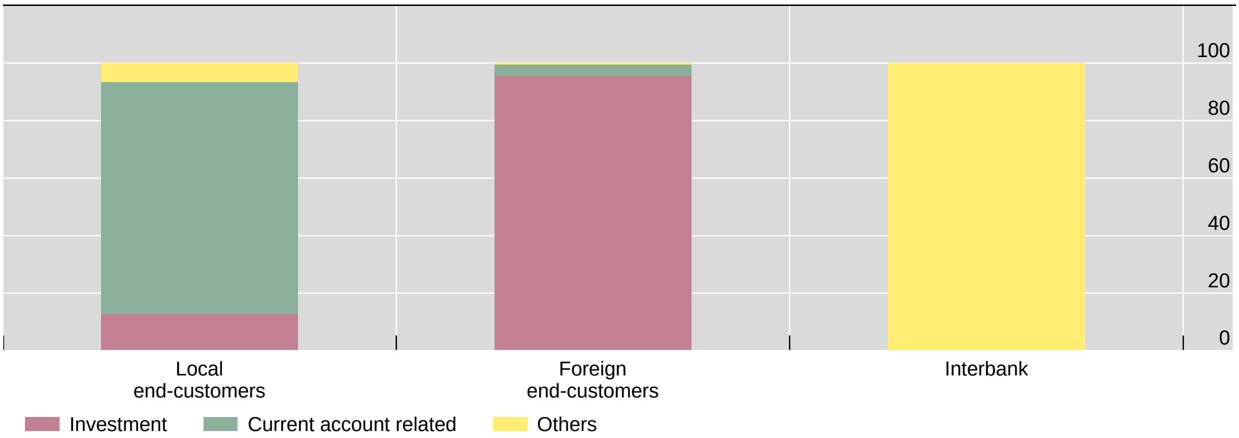
Other variables in our empirical analysis are constructed or obtained as follows. The realised FX volatility measures as well as the FX market return measure are constructed using spot USDTHB series obtained from Bloomberg.[13] Our implied volatility measure is the weekly average of daily USDTHB option-implied volatility series obtained from Bloomberg. To represent domestic and global monetary conditions, we use the weekly average of the daily values of the Thai policy rate and 10-year US Treasury yields, respectively. As a measure of global perception of risk, we follow the standard literature and use the weekly average of the daily VIX index. Data on both the interest rate variables and the VIX index are also obtained from Bloomberg. To capture the funding constraints faced by Thai market makers, we make use of BOT data on the inventory positions of dealer banks in Thailand. We expect that higher dollar position held by Thai banks should proxy their willingness to provide liquidity to the market.[14] Finally, the Thai bond and stock market volatilities are measured as intraweekly standard deviations, constructed by using data from the Thai Bond Market Association and Bloomberg, respectively.

[13] We only use USDTHB series in constructing measures of return and volatility, since the BOT dataset indicates that USDTHB trading volume accounts for roughly 90% of total spot trading volume over the years of 2010–2015.

[14] Ideally, data on the capital constraint faced by market-making banks would allow us to better capture the constraint that may limit these banks' ability to make markets. However, these data are not available on a high-frequency basis. In addition, consultation with the BOT seems to indicate that the capital constraint is not a binding constraint for most banks. Therefore, using dollar position may be a more appropriate measure to capture the banks' willingness to act as liquidity providers in the market.

Transaction purposes by key participant type

In per cent Graph 2



The graph only covers trading activity of the three key types of private participant in the market. The sample period is from 4 January 2010 to 18 March 2016.

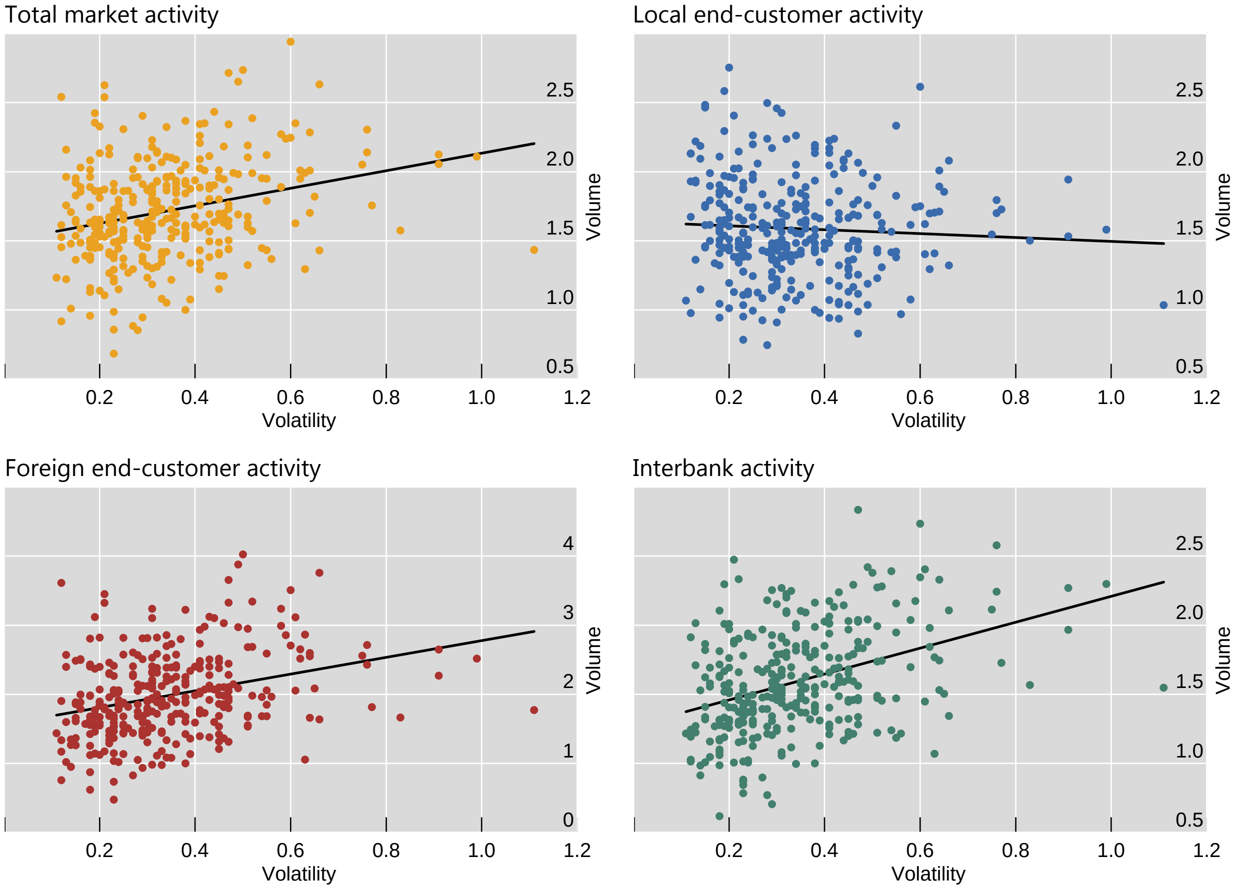
Sources: Bank of Thailand; authors' calculations.

With these data, Equation (1) is estimated using ordinary least squares (OLS). The sample period is from 4 January 2010 to 18 March 2016, which is the latest date when the BOT data were available at the start of this project. This makes the total number of weekly observations 324. To account for the possibility of non-standard errors, we use heteroscedasticity and autocorrelation consistent (HAC) standard errors. All variables are modelled in level after conducting augmented Dickey–Fuller (ADF) tests. The only exceptions are the interest rate variables, for which the null hypothesis of the ADF test cannot be rejected. We therefore model these variables as deviations from their one-month average values. A correlation analysis has been conducted to ensure that our results are not affected by multicollinearity problems.[15]

Before we proceed to the next section, as a prelude to our main empirical investigations, Graph 3 shows scatterplots of FX volatility against aggregate and participant-level volumes. At the aggregate level, we observe a clear positive association between volatility and volume. Although at this stage such an association can be a product of several endogeneity issues, the positive slope does provide promising evidence in support of the hypothesis being explored in this paper. At the participant-specific level, the scatterplots reveal that there is indeed significant heterogeneity in the volatility–liquidity relationship. Specifically, local volume appears to be negatively (albeit mildly) correlated with volatility, while foreign and interbank volumes are positively correlated. In the next section, we further investigate potential explanation for this difference, should it still exist conditional on other factors.

[15] As shown in Table A in Appendix 1, most of the independent variables do not have pairwise correlation coefficients higher than 0.2 in either the positive or negative directions. The only exceptions are the coefficients between 1) stock market volatility/bond market volatility and the VIX index, and 2) the VIX index and the US Treasury yield. However, dropping these variables one at a time does not change our main qualitative conclusions.

Scatter plots of USDTHB volatility and trading volume Graph 3



The sample period is from 4 January 2010 to 18 March 2016.

Sources: Bank of Thailand; authors' calculations.

5 Empirical results

5.1 Aggregate liquidity, market volatility and other determinants

To examine the relationship between aggregate market liquidity, market volatility and other determinants, we estimate three specifications of Equation (1). The first specification contains FX volatility as the only explanatory variable (which makes the regression result equivalent to the fitted line depicted in the scatterplot for total market activity in Graph 3). The second specification includes other potential factors. The third attempts to control for potential information-related confounding variables.

The regression results are reported in Table 1. The adjusted R-squared of the full specification is almost 0.4, indicating that the model performs reasonably well in explaining the time-series variations in the total trading volume of the Thai FX spot market. Overall, it is clear that such variations are induced by a number of factors, not least exchange rate volatility.

Consistent with the hypothesis being tested in this paper, the effect of FX market volatility on total trading volume in column (1) is significant and positive. The coefficient is also economically significant, with a one-standard deviation increase in

FX volatility leading to an increase of volume by around 20 percent of its one standard deviation. The result is robust to controlling for potential confounding variables, including market conditions in column (2) and information-related factors in column (3). Such evidence supports our hypothesis that there is a beneficial aspect to market volatility in so far as market liquidity is concerned.[16] Assuming that we have successfully controlled for information-related factors (an issue we investigate further in the robustness check section), the result also shows that volatility and volume may be more fundamentally related than suggested by Clark's (1973) mixture of distribution hypothesis.

Drivers of Thai FX liquidity: baseline results Table 1

Variable	(1)	(2)	(3)
FX Volatility	1355.24***	1309.24***	1083.56***
	(0.00)	(0.00)	(0.00)
Directional Movement		786.14***	711.52***
(Weekly Return)		(0.00)	(0.01)
Policy Rate		−38.32***	−36.59***
(Dev from 1M Avg)		(0.00)	(0.01)
UST 10Y		−14.14*	−16.91**
(Dev from 1M Avg)		(0.06)	(0.02)
VIX		−27.07**	−40.03***
		(0.02)	(0.00)
Banks' Net FX Position		0.43***	0.41***
		(0.00)	(0.00)
Stock Volatility			1722.86***
			(0.01)
Bond Volatility			−408.06
			(0.88)
Constant/Monthly Dummies	Yes/No	Yes/Yes	Yes/Yes
Adj. R-squared	0.07	0.33	0.37
Observations	324	324	324

Numbers in brackets are p-values. ***, ** and * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used. The full regression results of specification 3 are shown in Table B in Appendix 1.

Turning to other determinants of trading liquidity, we find that variations in trading liquidity in the Thai FX spot market are driven by several other factors. This is consistent with the finding in previous studies, such as Karnaukh et al (2015).

16 It is important to note that observing an increase in trading volume as a result of a rise in market volatility (or, equivalently, finding a positive coefficient on market volatility in our regression) does not necessarily imply that market volatility has a beneficial effect on trading volume/market liquidity (our "profit-making opportunity" story). It may be the case that volatility simply went in the direction that caused investors to start making losses, and their increased volume is simply a reflection of their attempt to cut losses by adjusting their positions (a "loss avoiding" story). While this scenario is entirely possible, when we further regress the bid-ask spread on market volatility and other covariates, we find no statistically significant relationship on market volatility. From this, we can argue that at least during our sample period, traders' volume adjustment following increased market volatility did not come at increased trading cost, as would be signified by a corresponding increase in the bid-ask spread. Therefore, the loss avoiding story appears unlikely during our sample period.

First, the regression results show that trading liquidity is influenced not only by the volatility of the exchange rate, but also by its directional movements. Specifically, aggregate volume is higher on average when the market is down than when it is up. Asymmetry in liquidity is previously documented by Chordia et al (2001) and Hameed et al (2010). However, these studies find the opposite kind of asymmetry that liquidity is higher in up markets than in down markets. Hameed et al's (2010) explanation for their finding is that in down markets liquidity providers are more likely to hit their capital constraints. Chordia et al (2001) conjecture that market makers may find it more difficult to adjust inventory in falling markets. In our case, since Thai banks are capitalised well above the required level, market makers may not be as constrained in down markets. On the contrary, it is possible that in the Thai case, traders may feel more pressed to monitor and adjust their positions more frequently in down markets.

Second, both domestic and global monetary conditions have a significant impact on market liquidity. As expected, liquidity is on average higher during monetary expansion than during monetary contraction. Based on the estimated coefficients, the effects of variations in domestic and global conditions are small but not immaterial: a one standard deviation increase in the variables leads to an increase in volume of around 16 and 13 percent of its one standard deviation, respectively. The significance of these monetary variables is consistent with the findings of past studies. Chordia et al (2003), for instance, find that domestic monetary expansion increases equity market liquidity. More broadly speaking, however, the result also highlights another important channel through which monetary policy implemented by advanced economies may potentially have spillovers on emerging market economies, above and beyond the more obvious, and much more documented, asset price channel.[17]

Risk appetite also has important implications for market liquidity, whether this is viewed from demand-side (global risk appetite, as proxied by the VIX) or supply-side (market makers' willingness to warehouse risks, as proxied by market-making banks' net FX positions) perspectives. Indeed, their economic significance appears to be greater than other factors examined above. For the demand side, a one standard deviation increase in the VIX index leads to a reduction in market volume equivalent to around 30 percent of its standard deviation. For the supply side, a one standard deviation increase in the net FX inventory held by the Thai banks translates to an increase in market volume of around 31 of its standard deviation. These results clearly highlight the empirical relevance of theoretical models in the literature that stress the importance of market risks to the determination of market liquidity, such as Brunnermeier and Pedersen (2009). They are also consistent with previous empirical studies, such as Bao et al (2008) and Mancini et al (2013).

Last, as shown in the full result table (Table B in Appendix 1), there appears to be no significant seasonal pattern in the evolution of the Thai FX spot market's total liquidity. This result contrasts with previous findings in the literature, such as Chordia et al (2001) who detect some seasonality in their data.

17 Miyajima et al (2014) show that US unconventional monetary policy had significant spillover effects on Asian markets, mainly through suppressing domestic bond yields and boosting domestic bank credit growth. Similarly, Koosakul (2016) shows that the long-end of the Thai yield curve is significantly affected by US monetary conditions and foreign flows into the domestic bond market.

5.2 Participant-level liquidity, market volatility and other determinants

The scatterplots in Graph 3 suggest that there may be significant participant-level heterogeneity in the volatility–liquidity relationship. In order to investigate this issue further, we re-estimate Equation (1) after replacing total volume by the participant-specific volume. Our approach is partly motivated by previous works in this area, which find that heterogeneity of players does matter to the volatility–liquidity relationship. For example, Bjonne et al (2003) find that the spot volume of large banks is especially important in influencing market volatility. Similarly, Daigler and Wiley (1999) document that trades by "speculators" located outside the market tend to be more correlated with volatility than those by investors in the market.

The regression results in Table 2 show significant heterogeneity, not only in terms of the impact of volatility on liquidity, but also in terms of the drivers of different players' trading activity in general. Overall, local participants' activity appears to be the least affected by market conditions, with the coefficients on most of the variables being statistically insignificant.[18] The adjusted R-squared of 0.05 is also small, indicating poor explanatory power of the model. This finding is, nonetheless, an expected outcome. In particular, as shown in Graph 2, local players engage in the Thai FX spot market mainly to facilitate their international trade operations. It is therefore no surprise that their activity is not driven by financial market factors, but rather derived from their export/import demands, which are not captured in the model.

Despite the insignificance of most variables, it is worth highlighting that market volatility remains a significant determinant of the activity of local participants. The coefficient is, however, negative, suggesting that local activity *decreases* when the market is volatile. This finding is also as expected, since local players do not participate in the market for return-motivated reasons. Instead, when the spot exchange rate becomes volatile, local participants may be inclined to switch from spot to forward transactions to settle their trade obligations in order to reduce their FX exposure.

By contrast, we find that foreign and interbank activity is significantly affected by several factors, consistent with the findings at the aggregate level. In particular, market volatility remains a significant and positive determinant of these players' activity. This result again highlights the potential beneficial effect that market volatility may have on market trading liquidity. Further, it also confirms our prior on the segments of market liquidity that volatility is expected to have a positive effect on – that is, the segments of market liquidity contributed to by return-motivated participants. According to Graph 2, these players are foreign end-customers in the Thai case. Interbank activity, while not as strongly return-motivated as foreign activity[19], also increases when the market becomes volatile. This potentially reflects

[18] Because of stationarity, the equation for local investor activity is estimated in first differences instead of in levels as is done with the other participants' activity. Following this, the interest rate variables are also modelled as first differences instead of deviations from their one-month historical average. Therefore, the coefficients in the local investor column are not strictly comparable to those in the other columns. Appendix Table C reports the results when the local investor activity equation is estimated in levels.

[19] Unlike foreign end-customers, interbank players engage in the market to earn intermediation profits rather than trading profits. This makes it a priori unclear whether volatility should have a positive effect on interbank activity through the mechanism explored in this paper.

the fact that increased foreign activity, which is positively correlated with volatility, also leads interbank players to be more active in their market segment.[20]

Drivers of Thai FX liquidity by investor type

Table 2

Variable	Total volume	Local	Foreign	Interbank
FX Volatility	1083.56***	−215.19**	714.44***	479.87***
	(0.00)	(0.03)	(0.00)	(0.00)
Directional Movement (Weekly Return)	711.52***	123.58	207.47	241.70***
	(0.01)	(0.20)	(0.20)	(0.00)
Policy Rate (Dev from 1M Avg)	−36.59***	−408.20	−12.41	−10.51***
	(0.01)	(0.15)	(0.17)	(0.01)
UST 10Y (Dev from 1M Avg)	−16.91**	−254.42	−4.62	−5.17**
	(0.02)	(0.29)	(0.27)	(0.05)
VIX	−40.03***	4.08	−14.07**	−15.40***
	(0.00)	(0.56)	(0.03)	(0.00)
Banks' Net FX Position	0.41***	−0.15	0.18***	0.11***
	(0.00)	(0.17)	(0.00)	(0.00)
Stock Volatility	1722.86***	239.28	687.87*	609.01***
	(0.01)	(0.29)	(0.07)	(0.00)
Bond Volatility	−408.06	−481.12	1038.24	614.21
	(0.88)	(0.65)	(0.48)	(0.51)
Constant/Monthly Dummies	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Adj. R-squared	0.37	0.05	0.28	0.45
Observations	324	324	324	324

Numbers in brackets are p-values. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. HAC standard errors are used. The full regression results are shown in Table B in Appendix 1.

6 Endogeneity, robustness checks and nonlinear effects

In this section, we further discuss the baseline results in relation to three related issues. First, we delve further into potential endogeneity issues that may have remained unaccounted for, or otherwise not made clear, in the baseline estimation. Second, we conduct additional regression analyses to assess the robustness of the baseline results to the choices of liquidity and volatility measures used. Last, we explore potential nonlinearity in the volatility–liquidity relationship, with a view that beyond certain levels of market volatility, the "fear factor" effect of market volatility could potentially dominate the positive effects documented in the baseline regression results.

[20] A somewhat complementary explanation is provided by a report by the Reserve Bank of Australia (2008). Under this explanation, an increase in market volatility causes dealers to be more concerned about inventory risk, which prompts them to pass on customer trades onto the interdealer market more rapidly than they would if the market were less volatile.

6.1 Potential endogeneity

In identifying the effect of volatility on volume, we have thus far assumed that our empirical procedures are not subject to endogeneity issues, at least not above and beyond what has been accounted for by our information arrival proxies. Nevertheless, there remains a possibility that there is still some endogeneity remaining to bias the estimation results.

First, it is possible that reverse causality is present. Market liquidity has been identified in a number of previous studies to have a material impact on market volatility. As per Friedman (1953)'s seminal work, deep markets inhabited by rational speculators can be less volatile than shallow ones. This is because whenever an asset's price deviates from its fundamental value, rational speculators would initiate trades in the direction that brings the price back to what is justified by the relevant fundamentals. Alternatively, as argued by Pagano (1989), in deep markets the liquidity demands of investors are so large and diverse that they tend to cancel one another out. The individual demands are therefore likely to have less impact on asset prices.

It is important to note that even if the above explanations were a valid characterisation of the impact of volatility on market liquidity in the Thai FX market, the qualitative conclusion reached in the previous section would remain little affected. This is because under the described scenarios, volume is expected to have a *negative* impact on volatility. The ensuing simultaneity bias would therefore be downward. In spite of this potential downward bias, the coefficients on market volatility in our baseline estimation remain *positive*. It is therefore safe to conclude that the conclusion reached in the previous section – that volatility has a significant positive effect on trading liquidity – is not driven by potential reverse causality.[21,22]

Second and perhaps more importantly, it is possible that our proxies for information arrivals are not capable of capturing all information releases that drive the contemporaneous co-movement between volatility and volume. That is, the mechanism described by the mixture of distribution hypothesis remains to bias our estimated coefficient on volatility upward. This scenario is possible since the information set that affects stock and bond prices may not necessarily be the same as the one that affects the exchange rate.[23]

[21] This does not hold for our finding on local investor activity. That is, the observed negative coefficient on volatility in the local investor activity specification could be due to the downward bias caused by reverse causality.

[22] Some observers of financial markets may argue that the effect of volume on volatility can well be positive. Specifically, an increase in one-sided market trading volume may prompt more investors to initiate trades in the same direction if they expect asset prices to continue their trend. This can then cause asset prices to change in the same direction even further. To account for the potential upward bias caused by this scenario, as well as to account for other endogeneity issues described below, we run an additional regression as shown in Equation (2). Since this regression essentially captures the effect of pre-determined volatility (which cannot be affected by contemporaneous market volume) on contemporaneous market volume, we argue that the qualitative conclusion of our paper is not sensitive to the presence of simultaneity bias, be it downward or upward.

[23] Another potential source of endogeneity, as some may rightly argue, is the omission of FX intervention in our set of control variables. To account for this possibility, we also run an additional regression that includes Bank of Thailand's intervention volume as a control variable. However, the qualitative conclusions of our paper remain unchanged.

To better separate the potential effect of information arrivals from any direct effect that volatility may have on volume, we re-estimate the baseline specifications in the following ways.

First, to better capture information arrivals into the market, we include additional variables in Equation (1). The first set of additional variables are Citi Economic Surprise Indices (CESI) for developed markets, the United States and Thailand, obtained from Bloomberg. The second additional variable, which further takes advantage of the BOT's rich dataset, is the absolute value of foreign order flows in the Thai FX spot market. The inclusion of the latter variable follows the established strand of literature on the information content of order flows. Specifically, according to the market microstructure literature on information friction, order imbalances in the market can be seen as a reflection of private information possessed by certain groups of market participants, which leads them to initiate one-sided orders to profit from such knowledge.[24] This theory suggests that order flows should be a very useful measure of information arrivals in the market.

Second, and more systematically, we attempt to *separate* the contemporaneous effect of market volatility, which is subject to omitted variable bias, from the intertemporal effects of volatility. More specifically, we follow Galati (2001) in splitting the volatility measure into the expected and unexpected components, as shown in the following equation[25]:

$$liquidity_t = \theta_0 + \theta_1\, ex\_volatility_t + \theta_2\, unex\_volatility_t + \boldsymbol{X_t}\boldsymbol{\gamma} + \nu_t\,, \qquad (2)$$

where $ex\_volatility_t$ and $unex\_volatility_t$ are, respectively, the expected and unexpected components of exchange rate volatility, obtained by means of an autoregressive (AR) model.[26]

Our identification strategy for the second approach is the following. Under the information arrival story, only the *unexpected* component of market volatility – that is, the component that the market participants entering the current period did not anticipate given information in the previous periods – should be correlated with information releases. On the other hand, the *expected* component – which has already been pre-determined based on the information set in previous periods – should *not* be correlated with new information released in the current period. Accordingly, the coefficient on this component should be free from any potential upward bias. Therefore, if it is the case that the coefficient on this component remains positive and significant, we can claim that the information story does not play a role in confounding our result.

24 This line of reasoning is in the spirit of Bagehot (1971), Glosten and Milgrom (1985) and Kyle (1985), which argue that order flows have significant permanent effect on asset prices because they reveal private information to market dealers.

25 Although similar in approach, the difference between Galati (2001) and our paper is that ours focuses on the expected component of volatility, whereas Galati (2001) emphasises the unexpected component since he intends to empirically test the mixture of distribution hypothesis.

26 An AR(2) specification is chosen to model the FX volatility series based on suggestions by both the Akaike Information Criteria (AIC) and Schwartz Information Criteria (SIC).

The estimation results for our first approach is reported in Table 3.[27] We find that both CESIs and foreign FX order flows are indeed helpful in capturing elements of economic surprises in the Thai FX market that are not already reflected in our information arrival proxies.[28] The coefficients on the CESI and order-flow variables are statistically significant and positive, as expected under the mixture of distribution hypothesis. More importantly, the coefficients on FX volatility, while smaller in magnitude, remain significant and positive.[29] This finding provides further evidence in support of our hypothesis that the positive coefficient on market volatility reflects a more causal relationship than implied by the current market microstructure.

Exploring additional information-related variables Table 3

Variable	Total		Foreign		Interbank	
FX Volatility	1062.92***	922.49***	699.49***	612.35***	479.27***	447.51***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Thai Stock Market Volatility	1592.70**	1544.17***	591.03	574.61*	565.87***	573.11***
	(0.01)	(0.01)	(0.12)	(0.09)	(0.00)	(0.00)
Thai Bond Market Volatility	–417.53	–938.26	945.57	702.18	540.09	507.68
	(0.87)	(0.71)	(0.45)	(0.60)	(0.52)	(0.57)
CESI for Thailand	–0.16		–0.14		–0.24	
	(0.82)		(0.73)		(0.18)	
CESI for the US	5.52***		3.11**		1.85*	
	(0.01)		(0.01)		(0.10)	
CESI for Developed Markets	8.29**		5.97**		1.58***	
	(0.04)		(0.01)		(0.00)	
Foreign FX Order Flow		2.09***		1.32***		0.42***
		(0.00)		(0.00)		(0.00)
Constant/Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	0.36	0.42	0.27	0.36	0.44	0.45
Observations	324	324	324	324	324	324

Numbers in brackets are p-values. ***, ** and * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used. The CESI for developed markets series is first regressed on the CESI for US series, so that the post-transformed series reflects economic surprises above and beyond those from US news.

Table 4 reports the regression results for our second approach. It shows that the coefficients on unexpected FX volatility are significant and positive. This again potentially reflects the possible positive bias that remains present because of the

[27] The local activity specification is not estimated since the coefficient on volatility was already negative in spite of the potential remaining upward bias explored in this section.

[28] We use absolute values of CESI, since economic surprises in both positive and negative directions should have the same sign of effect on market volume and volatility.

[29] Including CESI one at a time, or dropping our initial information arrival proxies – stock and bond market volatilities – does not change the results qualitatively.

imperfect nature of our information arrival proxies.[30] More importantly, the coefficients on expected volatility are also significant and positive. In fact, the relative magnitude of the coefficients on the two components suggests that it is the expected component that has a stronger impact on market activity.[31] While these results do not strongly establish the direction of causality from volatility to market liquidity, when coupled with the argument that the bias arising from reverse causality in our case is likely to be downward, they provide support to our conclusion in the baseline specifications that market volatility have a positive causal impact on market volume.

Drivers of Thai FX liquidity: expected volatility — Table 4

Variable	Total	Foreign	Interbank
Expected FX Volatility	3620.60***	2286.98***	1315.11***
	(0.00)	(0.00)	(0.00)
Unexpected FX Volatility	626.51**	433.53**	329.23***
	(0.02)	(0.01)	(0.00)
Directional Movement	562.10**	118.03	192.78**
(Weekly Return)	(0.04)	(0.50)	(0.02)
Policy Rate	−33.16***	−10.26	−9.38***
(Dev from 1M Avg)	(0.00)	(0.18)	(0.00)
UST 10Y	−17.28***	−4.91	−5.32**
(Dev from 1M Avg)	(0.01)	(0.19)	(0.02)
VIX	−35.58***	−11.36*	−13.96***
	(0.00)	(0.07)	(0.00)
Banks' Net FX Position	0.43***	0.20***	0.11***
	(0.00)	(0.00)	(0.00)
Stock Market Volatility	1293.88**	429.04	468.70***
	(0.03)	(0.22)	(0.01)
Bond Market Volatility	291.33	1388.66	844.19
	(0.91)	(0.28)	(0.32)
Constant/Monthly Dummies	Yes/Yes	Yes/Yes	Yes/Yes
Adj. R-Squared	0.37	0.30	0.47
Observations	322	322	322

Numbers in brackets are p-values. ***, ** and * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used.

A conceptually similar approach involves adding lagged volatility to examine if previous volatility levels, which should be free from bias arising from contemporaneous information arrivals, also have an influence on the level of market liquidity in the contemporaneous period, given that traders' decisions should also depend on information on past market conditions. Including the first lag of USDTHB volatility into Equation (1), we find that both the contemporaneous and lagged values of market volatility have a significant positive effect on volume, again confirming our

[30] Or it is possible that the contemporaneous movement in volatility that is not expected given past values of volatility does have a positive impact on volume. Without further econometric analyses, however, this possibility cannot be validated.

[31] This is true even after standardising by the standard deviations of the two components.

hypothesis. The estimation results are not reported here to conserve space, but available upon request.

Finally, in order to consider the interaction of FX volatility and trading volume and the dynamic impact of volatility, we run VAR regressions with FX volatility, trading volume and FX returns as endogenous variables. Appendix 2 provides details on our VAR analysis. After trying possible orderings of endogenous variables, we find that the effect of FX volatility on trading volume is not just positive but also persistent up to four weeks. By contrast, we find much weaker evidence on the effect of trading volume on FX volatility.

6.2 Alternative measures of market activity and volatility

Our baseline specification uses trading volume and range volatility as a measure of market activity and exchange rate variability, respectively. These choices follow several previous papers that also use such measures in their study of the volume–volatility relationship.[32] In this subsection, we explore whether our baseline results are robust to alternative measures of market activity and volatility.

6.2.1 Alternative measures of market activity

As alternative measures of market activity, we use average trading frequency and average transaction size. The regression results for these alternative measures are reported in Table 5.[33] We find that changing from volume to frequency does not change our qualitative results on the positive effect of market volatility, with respect to both foreign and interbank activities.[34] The majority of the results on other drivers of market activity also remain unchanged. One interesting exception is that banks' market-making appetite no longer plays a role in influencing market activity when it is measured by average trading frequency. This result can be justified by the possibility that, so long as banks are willing to provide liquidity to the market, liquidity demanders can always ask banks to increase their order size without having to initiate multiple orders.

Average transaction size is a useful indicator of market liquidity as it affects the time it takes for a trader to build up or run down his position. Interestingly, average transaction size, unlike the other two measures, does not vary much with market conditions; Table 5 shows that almost all the market variables are statistically insignificant. A potential explanation for this finding is that transaction size reflects long-term, structural features of the market, such as market conventions and practices and dealer trading limit, rather than short-term market movements.

One notable exception is the significant effect of volatility on interbank transaction size. The coefficient on volatility is negative, indicating that average

32 Examples of studies that use such measures are Bauwens et al (2005) and Rime and Sucarrat (2007).

33 We do not re-estimate the total activity specification since, unlike the case for volume, the number of transactions by a certain type of participant far dominates those of the other two types. This seems to have influenced the results for the average size specification.

34 Because of the stationarity issue, the equation for local investor activity in Table 5 is estimated in first differences instead of in levels as is done with the other participants' activity. Therefore, the coefficients in the local investor column are not strictly comparable to those in the other columns. Appendix Table D provides the regression results when the local investor activity equation is estimated in levels.

transaction size in the interbank market decreases when the market becomes more volatile. This finding is consistent with the inventory model of market making (eg Stoll (1978), and Ho and Stoll (1981)), which suggests that market makers are less inclined to provide liquidity when liquidation risk is high. This finding, combined with the baseline results, implies that while higher market volatility boosts interbank trading volume, it also leads banks to reduce their average transaction size (ie break down a large-sized transaction into small-sized transactions) due to higher inventory risk.

Drivers of Thai FX liquidity: alternative measures of market activity — Table 5

Variable	Average frequency			Average size		
	Local	Foreign	Interbank	Local	Foreign	Interbank
FX Volatility	−161.01	318.14***	306.28***	−46.20*	−431.25	−1864.49***
	(0.74)	(0.00)	(0.00)	(0.07)	(0.37)	(0.00)
Directional Movement (Weekly Return)	679.23	154.55***	110.45***	9.19	−281.11	−71.65
	(0.16)	(0.00)	(0.00)	(0.82)	(0.68)	(0.91)
Policy Rate (Dev from 1M Avg)	15.78	−7.97***	−6.85***	−162.01	23.65	29.76
	(0.70)	(0.00)	(0.00)	(0.12)	(0.41)	(0.10)
UST 10Y (Dev from 1M Avg)	−1129.20	−2.09*	−2.51**	−11.59	7.98	6.76
	(0.33)	(0.09)	(0.01)	(0.85)	(0.64)	(0.66)
VIX	15.78	−7.97***	−6.85***	0.70	−1.97	−1.19
	(0.70)	(0.00)	(0.00)	(0.71)	(0.92)	(0.95)
Banks' Net FX Position	−0.38	0.00	−0.01	0.01	0.45***	0.39***
	(0.46)	(0.68)	(0.47)	(0.72)	(0.00)	(0.00)
Stock Market Volatility	1163.96	140.30	89.60	19.82	2004.03*	2875.18**
	(0.26)	(0.12)	(0.15)	(0.84)	(0.10)	(0.04)
Bond Market Volatility	−2168.50	758.16	553.62	25.36	−1283.77	−2163.18
	(0.74)	(0.11)	(0.19)	(0.94)	(0.85)	(0.75)
Constant/Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	−0.03	0.50	0.55	0.05	0.15	0.25
Observations	324	324	324	324	324	324

Numbers in brackets are p-values. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC errors are used. Local specifications are estimated in first differences in light of the stationarity issue. The coefficients for the average size specifications are multiplied by 10000 for the purpose of presenting the coefficients in the table in the same format as the others. This conversion is equivalent to changing the unit of the average size from million dollars to hundred dollars.

6.2.2 Alternative measures of market volatility

We use the following three alternative volatility measures to test the robustness of our results: (1) another measure of intraweek volatility, namely within-week standard deviation of USDTHB; (2) a longer-term measure of volatility, namely exponentially-weighted moving average (EWMA) volatility; and (3) a volatility measure that incorporates forward-looking elements, namely, option-implied USDTHB volatility.

Table 6 reports a summary of the sign and significance of the coefficient on FX volatility when the previous results are re-estimated using alternative measures of volatility. Green (red) coloured cells represent that the coefficient on market volatility is statistically significantly positive (negative). Grey coloured cells represent that the coefficient is not statistically significant. Table 6 shows that most of our results are indeed robust to alternative measures of volatility used. Interestingly, the only sets of results that are not robust are the ones that find the negative effect of market volatility, namely the findings on local investor activity in the baseline result section and on interbank activity in the previous subsection. By contrast, the results on the positive effect of volatility are otherwise generally robust.

Sign and significance of the coefficient on alternative measures of volatility — Table 6

Measure of Activity	Entity Type	Baseline	Intraweek SD	EWMA	Implied Vol
Transaction Volume	Total				
	Local				
	Foreign				
	Interbank				
Transaction Frequency	Local				
	Foreign				
	Interbank				
Transaction Size	Local				
	Foreign				
	Interbank				

Green (red) coloured cells represent that the coefficient on market volatility is statistically significantly positive (negative). Grey coloured cells represent that the coefficient is not statistically significant.

6.3 Nonlinearity in the impact of volatility on trading volume

So far we considered the volatility–activity relationship based on the assumption that the relationship is linear, and showed that volatility has a beneficial effect on market activity by increasing the scope for potential profit making.

However, we conjecture that the positive relationship might hold until a certain level of market volatility. Beyond such a threshold, it is possible that the more "vicious" aspects of market volatility explored in the existing studies (eg Pagano (1989) and Brunnermeier and Pedersen (2009)) may become dominant in characterising the volatility–liquidity relationship. Empirically, Reserve Bank of Australia (2007) finds a nonlinear relationship in the Australian FX market. In particular, the study notes that while the volatility–turnover relationship is positive in normal periods in the Australian case, the relationship generally turns negative when the market comes under stress, such as during the 2007 global credit market turmoil which coincided with rapid movements in the US dollar–Australian dollar exchange rate and the US dollar–New Zealand dollar exchange rate and rapid deterioration in market liquidity.

With this motivation, we explore the nonlinear relationship between market volatility and trading volume. In doing so, we identify periods of high market volatility as those when the values of FX volatility are above the 95th and 99th percentiles.[35] After identifying such periods, we create a dummy variable equal to 1 for the week that corresponds to such periods, and zero otherwise. We then re-estimate the effect of market volatility on market activity using the following specification:

[35] While these percentiles are rather high, given that our sample period corresponds to a relatively stress-free period, we view that they are appropriate in capturing periods of unusually high volatility.

$$liquidity_t = \rho_0 + \rho_1 volatility_t + \rho_2 volatility_t * D_t + \boldsymbol{X_t \omega} + \eta_t \, , \quad (3)$$

where $D_t$is the dummy variable described above. Therefore, $\rho_1 + \rho_2$ captures the net effect of market volatility when volatility falls into the percentiles.

The regression results are reported in Table 7.[36] We find evidence that nonlinearity exists in the volatility–liquidity relationship. In particular, when market volatility becomes sufficiently high, the liquidity-enhancing effect of volatility greatly diminishes, consistent with the fear factor story discussed above. However, the *net* effect of volatility on volume remains positive. This may have to do with our sample period corresponding to a relatively tranquil period.[37] In sum, we show that on average, market volatility has a significant positive effect on market activity, possibly through increasing the scope for profit making, but that at high levels of volatility, this effect becomes less relevant as other negative aspects of market volatility explored in several existing studies start kicking in.

Drivers of Thai FX liquidity – nonlinear effects Table 7

Variable	Total Volume	Local	Foreign	Interbank
95th percentile				
FX Volatility	1400.78***	−295.11**	1010.46***	604.83***
	(0.00)	(0.01)	(0.00)	(0.00)
FX Volatility 95	−436.08	273.65	−406.95**	−171.78**
X FX Volatility	(0.16)	(0.25)	(0.04)	(0.05)
Adj. R-Squared	0.37	0.06	0.29	0.46
99th percentile				
FX Volatility	1312.45***	−242.79**	872.63***	533.63***
	(0.00)	(0.04)	(0.00)	(0.00)
FX Volatility 99	−822.10**	198.80	−568.16***	−193.10*
X FX Volatility	(0.01)	(0.45)	(0.00)	(0.06)
Adj. R-Squared	0.37	0.05	0.29	0.46

Numbers in brackets are p-values. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively. HAC errors are used. Local specification is estimated in first differences to ensure stationarity. Because of this, the dummy variable for this specification is also changed to match the first differences model. Specifically, the dummy variable takes the value of one if the change in volatility exceeds the 95th and 99th percentiles of the sample period values. The coefficients on the constant and the control variables are not reported to conserve space, but are available upon request.

[36] Given that our sample period does not include a major financial crisis in the United States and Thailand, some may argue that modelling potential nonlinearity in the volatility–liquidity relationship in weekly frequency makes it even less likely to uncover the negative aspect of market volatility. Since any period of market "stress" that may be present on a daily basis in our sample period is not likely to be sustained over the entire week, using weekly frequency may lead us to misidentify highly turbulent, but otherwise short-lived, events in our sample period. In light of this caveat, and because modelling in daily frequency allows us to have more data points of turbulent periods by construction, we also re-estimate Equation (3) in daily frequency. The regression results, which are not reported in this paper but available upon request from the authors, show that the qualitative conclusions reached in this section are robust when we use daily data instead of weekly data.

[37] There are certainly some episodes of high market volatility, such as the "taper tantrum" period in May 2013, in our sample period. However, it can be argued that these events are relatively mild compared to what can be considered crisis periods, such as the Asian financial crisis of 1997–98 and immediately after the Lehman bankruptcy in 2008.

7 Conclusion

This paper contributes to the literature on the volatility–liquidity relationship by showing the beneficial effect of exchange rate volatility on FX market liquidity measured by trading volume in the USDTHB spot market. This empirical finding is in line with theoretical models developed by Herrera (2005) and Jeanne and Rose (2002), which show that in the presence of entry cost, market volatility is one of the key factors that market participants consider when assessing the relative cost and benefit of participating in a particular market. The main intuition is that, if the market is not adequately volatile, there may not be sufficient potential gain from trading to justify entry. We also find significant heterogeneity in the relationship between exchange rate volatility and FX market liquidity across different types of market participant. We obtain consistent results when we control for endogeneity, consider potential dynamics and use alternative variables for market volatility and liquidity. Finally, we find evidence of nonlinearity in the volatility–liquidity relationship.

Our results show that the net effect of volatility on aggregate market activity is significant, positive, persistent and causal. This finding is important from both positive and normative standpoints. From a positive standpoint, the positive relationship between volatility and trading volume has thus far often been argued to be non-causal, as viewed through the lens of the mixture of distribution hypothesis (Clark (1973)). By controlling for information-related confounding variables, we show that there may be a more causal mechanism to this relationship than suggested by Clark (1973). From a normative standpoint, our findings suggest that policy actions to reduce volatility in the FX market may be beneficial in some circumstances, but not in all. In particular, at high levels of market volatility, the negative aspects of market volatility, such as the volatility–liquidity spiral explored by Pagano (1989), are likely to be strong relative to the positive aspect. Hence, exchange rate stabilisation policies may have a beneficial effect. At normal levels of market volatility, however, such policies may reduce exchange rate volatility too much, deprive market participants of potential profit making opportunities, and thus erode market liquidity.

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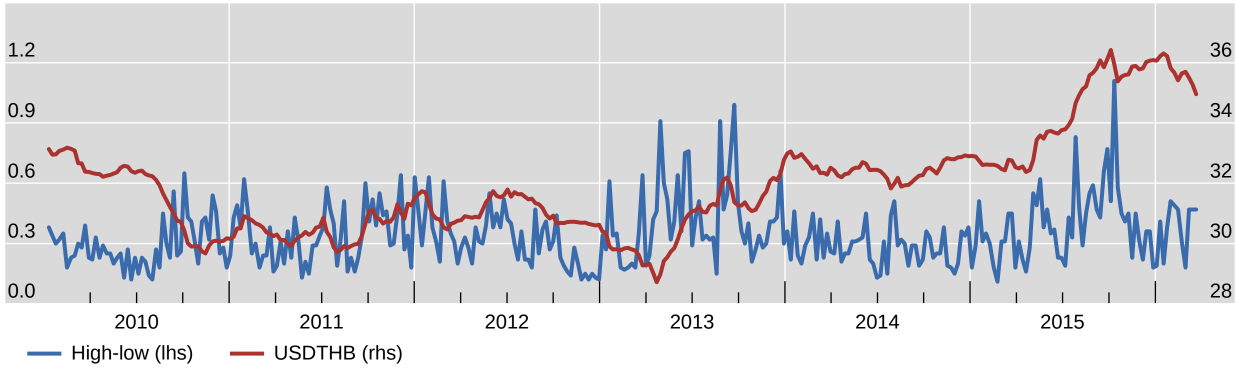
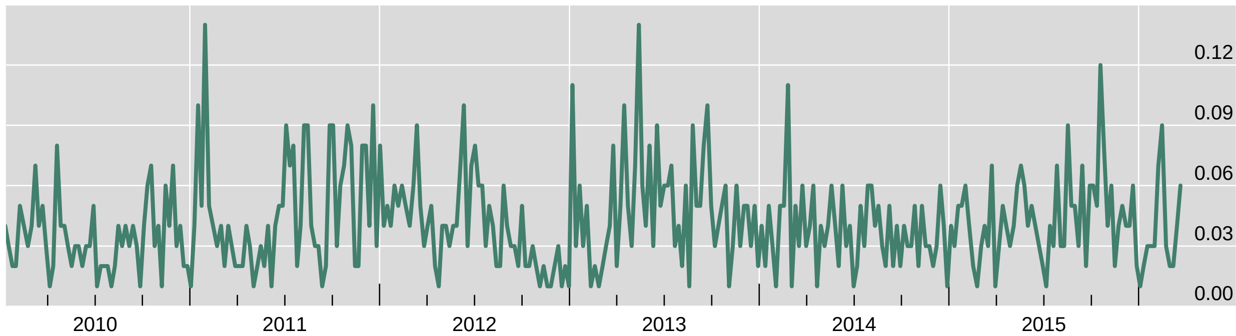
Appendix 1: Additional graphs and tables

Different measures of USDTHB volatilities — Graph A

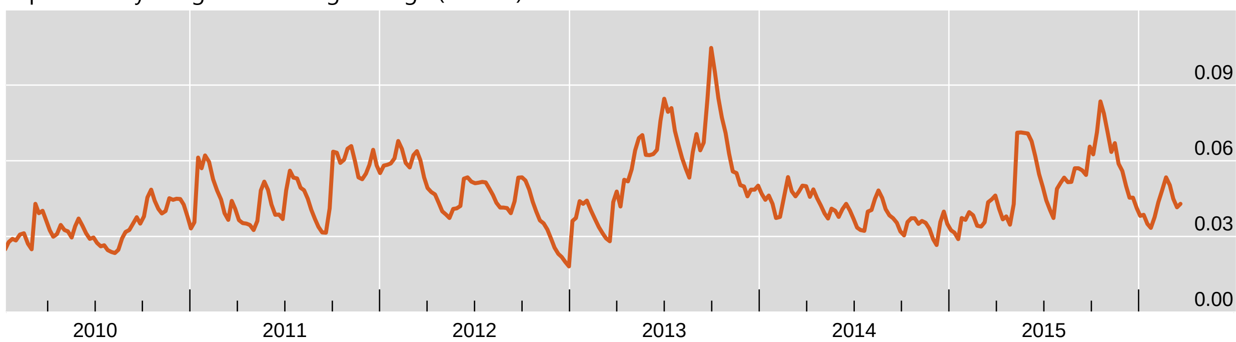
High–low and USDTHB



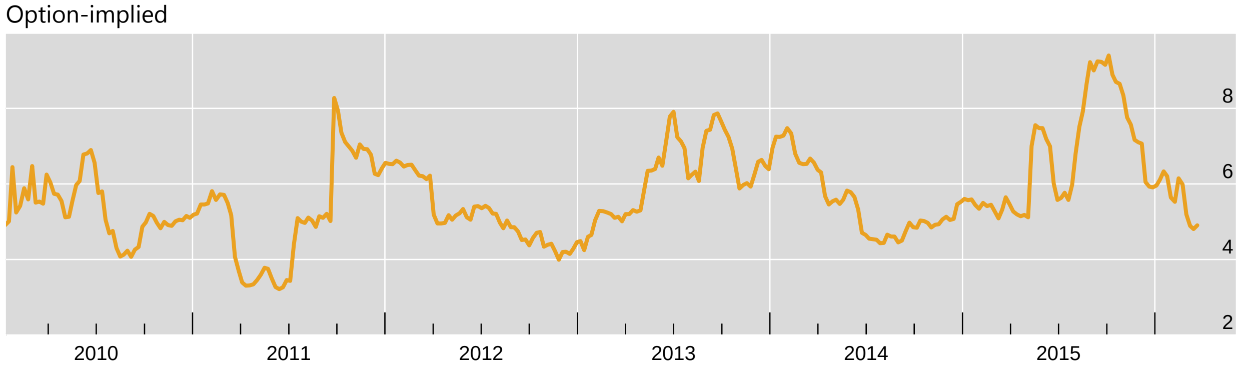
Intraweek standard deviation



Exponentially-weighted moving average (EWMA)



Option-implied



Sources: Bloomberg; authors' calculations.

Correlation among variables

Appendix Table A

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Total Volume											
(2) Foreign Volume	0.90										
(3) Local Volume	0.66	0.33									
(4) Interbank Volume	0.85	0.73	0.34								
(5) USDTHB Volatility	0.27	0.31	−0.06	0.38							
(6) USDTHB Returns	0.17	0.09	0.17	0.17	0.01						
(7) Policy Rate*	−0.20	−0.14	−0.17	−0.19	−0.14	−0.10					
(8) 10Y UST Yield*	−0.01	0.01	−0.04	0.00	0.04	0.06	−0.15				
(9) VIX	−0.24	−0.16	−0.21	−0.24	0.03	0.00	0.20	−0.38			
(10) Banks' Inventories	0.35	0.28	0.28	0.29	−0.06	−0.02	0.01	0.01	−0.17		
(11) Stock Price Volatility	0.19	0.17	0.08	0.21	0.26	0.10	0.01	−0.05	0.34	0.05	
(12) Bond Price Volatility	0.13	0.17	−0.09	0.20	0.27	0.11	−0.11	0.08	0.12	0.06	0.34

Variables with * are modelled as deviations from one-month moving average. The colours reflect the relative magnitude of the pairwise correlations: darker green (red) colours represent higher positive (negative) correlation coefficients compared to lighter green (red).

Full results from the baseline regression

Appendix Table B

Variable	Total	Local	Foreign	Interbank
Constant	3259.95***	–47.32	997.27***	833.33***
	(0.00)	(0.46)	(0.00)	(0.00)
FX Volatility	1083.56 ***	–215.19**	714.44***	479.87***
	(0.00)	(0.03)	(0.00)	(0.00)
Directional Movement	711.52***	123.58	207.47	241.70***
(Weekly Return)	(0.01)	(0.20)	(0.20)	(0.00)
Policy Rate	–36.59***	–408.20	–12.41	–10.51***
(Dev from 1M Avg)	(0.01)	(0.15)	(0.17)	(0.01)
UST 10Y	–16.91**	–254.42	–4.62	–5.17**
(Dev from 1M Avg)	(0.02)	(0.29)	(0.27)	(0.05)
VIX	–40.03***	4.08	–14.07**	–15.40***
	(0.00)	(0.56)	(0.03)	(0.00)
Banks' Net FX Position	0.41***	–0.15	0.18***	0.11***
	(0.00)	(0.17)	(0.00)	(0.00)
January	–37.57	49.72	36.22	147.64**
	(0.84)	(0.33)	(0.76)	(0.01)
February	–94.11	87.48	30.07	107.66*
	(0.72)	(0.11)	(0.85)	(0.08)
March	–103.59	22.22	43.94	68.78
	(0.60)	(0.65)	(0.71)	(0.20)
April	14.53	98.74*	56.54	37.40
	(0.95)	(0.08)	(0.68)	(0.52)
May	16.62	–26.44	34.60	157.24***
	(0.93)	(0.62)	(0.78)	(0.01)
June	–167.21	90.08*	–124.34	79.20
	(0.30)	(0.06)	(0.22)	(0.11)
July	120.25	55.36	58.19	176.07***
	(0.59)	(0.35)	(0.70)	(0.00)
August	255.13	16.23	186.17*	251.56***
	(0.12)	(0.78)	(0.08)	(0.00)
September	111.51	51.24	62.17	179.95***
	(0.56)	(0.37)	(0.59)	(0.01)
October	–180.05	18.66	–76.09	57.83
	(0.32)	(0.75)	(0.50)	(0.37)
November	–239.02	100.13	–99.77	45.96
	(0.12)	(0.12)	(0.29)	(0.44)
Stock Market Volatility	1722.86 ***	239.28	687.87*	609.01***
	(0.01)	(0.29)	(0.07)	(0.00)
Bond Market Volatility	–408.06	–481.12	1038.24	614.21
	(0.88)	(0.65)	(0.48)	(0.51)
Adj. R-Squared	0.37	0.25	0.28	0.45
Observations	324	324	324	324

Numbers in brackets are p-values. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used.

Drivers of Thai FX liquidity by investor type – local investor specification modelled in levels

Appendix Table C

Variable	Local	Foreign	Interbank
FX Volatility	−110.75	714.44***	479.87***
	(0.18)	(0.00)	(0.00)
Directional Movement (Weekly Return)	262.34***	207.47	241.70***
	(0.00)	(0.20)	(0.00)
Policy Rate (Dev from 1M Avg)	−13.66***	−12.41	−10.51***
	(0.00)	(0.17)	(0.01)
UST 10Y (Dev from 1M Avg)	−7.11***	−4.62	−5.17**
	(0.01)	(0.27)	(0.05)
VIX	−10.56***	−14.07**	−15.40***
	(0.00)	(0.03)	(0.00)
Banks' Net FX Position	0.12***	0.18***	0.11***
	(0.00)	(0.00)	(0.00)
Stock Market Volatility	425.98**	687.87*	609.01***
	(0.01)	(0.07)	(0.00)
Bond Market Volatility	−2060.50**	1038.24	614.21
	(0.04)	(0.48)	(0.51)
Constant/ Monthly Dummies	Yes/Yes	Yes/Yes	Yes/Yes
Adj. R-Squared	0.25	0.28	0.45
Observations	324	324	324

Numbers in brackets are p-values. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used.

Drivers of Thai FX liquidity by investor type: alternative measures of market activity – local investor specification modelled in levels

Appendix Table D

Variable	Average frequency			Average size		
	Local	Foreign	Interbank	Local	Foreign	Interbank
FX Volatility	−381.10	318.14***	306.28***	−59.49***	−431.25	−1864.49***
	(0.22)	(0.00)	(0.00)	(0.00)	(0.37)	(0.00)
Directional Movement (Weekly Return)	1278.91***	154.55***	110.45***	16.03	−281.11	−71.65
	(0.00)	(0.00)	(0.00)	(0.53)	(0.68)	(0.91)
Policy Rate (Dev from 1M Avg)	−62.62***	−7.97***	−6.85***	−1.73***	23.65	29.76
	(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.10)
UST 10Y (Dev from 1M Avg)	−33.45***	−2.09*	−2.51**	−0.52	7.98	6.76
	(0.01)	(0.09)	(0.01)	(0.32)	(0.64)	(0.66)
VIX	−73.73***	−7.97***	−6.85***	−1.02	−1.97	−1.19
	(0.00)	(0.00)	(0.00)	(0.10)	(0.92)	(0.95)
Banks' Net FX Position	−0.15*	0.00	−0.01	0.02***	0.45***	0.39***
	(0.07)	(0.68)	(0.47)	(0.00)	(0.00)	(0.00)
Stock Market Volatility	1520.72**	140.30	89.60	108.86*	2004.03*	2875.18**
	(0.03)	(0.12)	(0.15)	(0.06)	(0.10)	(0.04)
Bond Market Volatility	−1720.05	758.16	553.62	−237.53	−1283.77	−2163.18
	(0.73)	(0.11)	(0.19)	(0.41)	(0.85)	(0.75)
Constant/Monthly Dummies	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes	Yes
Adj. R-Squared	0.22	0.50	0.55	0.28	0.15	0.25
Observations	324	324	324	324	324	324

Numbers in brackets are p-values. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. HAC standard errors are used. The coefficients for the average size specifications are multiplied by 10000 for the purpose of presenting the coefficients in the table in the same format as the others. This conversion is equivalent to changing the unit of the average size from million dollars to hundred dollars.

Appendix 2: VAR analysis

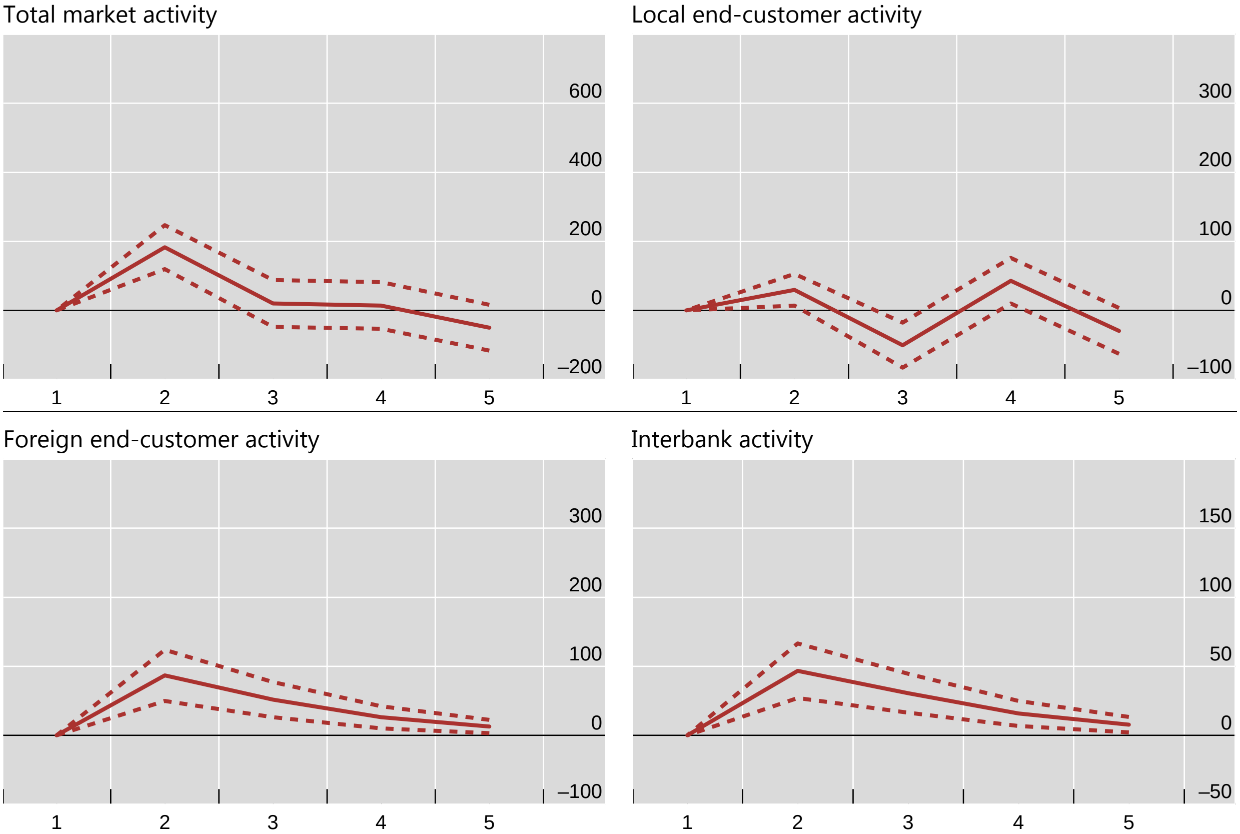
In order to consider the interaction of FX volatility and trading volume and the dynamic impact of volatility, we run VAR regressions with FX volatility and trading volume and compute impulse responses using the standard Cholesky scheme. When we specify VAR regressions, we also include the FX return variable as another potentially endogenous variable, following a similar set of variables used in Chordia et al (2003), who also investigate the relationships between market volatility and liquidity using a VAR approach. We include all other variables in Equation (1) in the exogenous variable set.

Before we run a VAR regression, we determine the lag order of VAR by the Schwarz information criteria where up to five lags are considered. The optimal lag length is one for total trading volume and local investors' trading volume, while that for foreign and interbank investors' trading volume is four.

We start with a VAR specification where FX volatility is ordered last in the system. In other words, we assume that the volatility responds immediately to all the shocks in the system, but that a volatility shock can affect the other variables only with a lag. Through this identification scheme, we endogenise FX volatility as much as possible, thus minimising any potential remaining endogeneity issues in the estimated effect of FX volatility on trading volume to the extent possible. For the other two endogenous variables, we order trading volume first and then FX return. The impulse responses in Graph B show that there is indeed some persistence in the positive effect of volatility on trading volume, and that the effect is especially strong for foreign and interbank volumes up to four weeks. We also switch the order between volatility and FX return, but the results remain the same. Finally, when we order liquidity last and volatility first, Graph C shows that the positive results for volatility are stronger. Therefore, we can conclude that FX volatility has a persistent dynamic effect on the trading volume of foreign and interbank investors.

Our VAR regression results also shed light on the extent of reverse causality; that is, the effect of FX trading volume on FX volatility. In contrast to the strong evidence of a persistent positive effect of FX volatility on trading volume, we find much weaker evidence on the effect of trading volume on FX volatility. In particular, when we order trading volume first as an exogenous variable, we find a significant positive response of volatility to foreign and interbank trading volume up to three weeks. By contrast, when we order trading volume last as an endogenous variable, we do not find a significant positive response of volatility to any type of trading volume. It is possible that, by disallowing the contemporaneous channel through which trading volume affects volatility, as is done in the second case, we have effectively "muted" the information arrival channel through which trading volume can positively affect volatility. With this channel closed, our regression results suggest that trading volume does not have a significant impact on market volatility. This finding provides another assurance that our baseline regressions are not materially prone to simultaneity bias to begin with. The VAR regression results on the impulse responses of volatility to trading volume are not reported here to conserve space, but are available upon request.

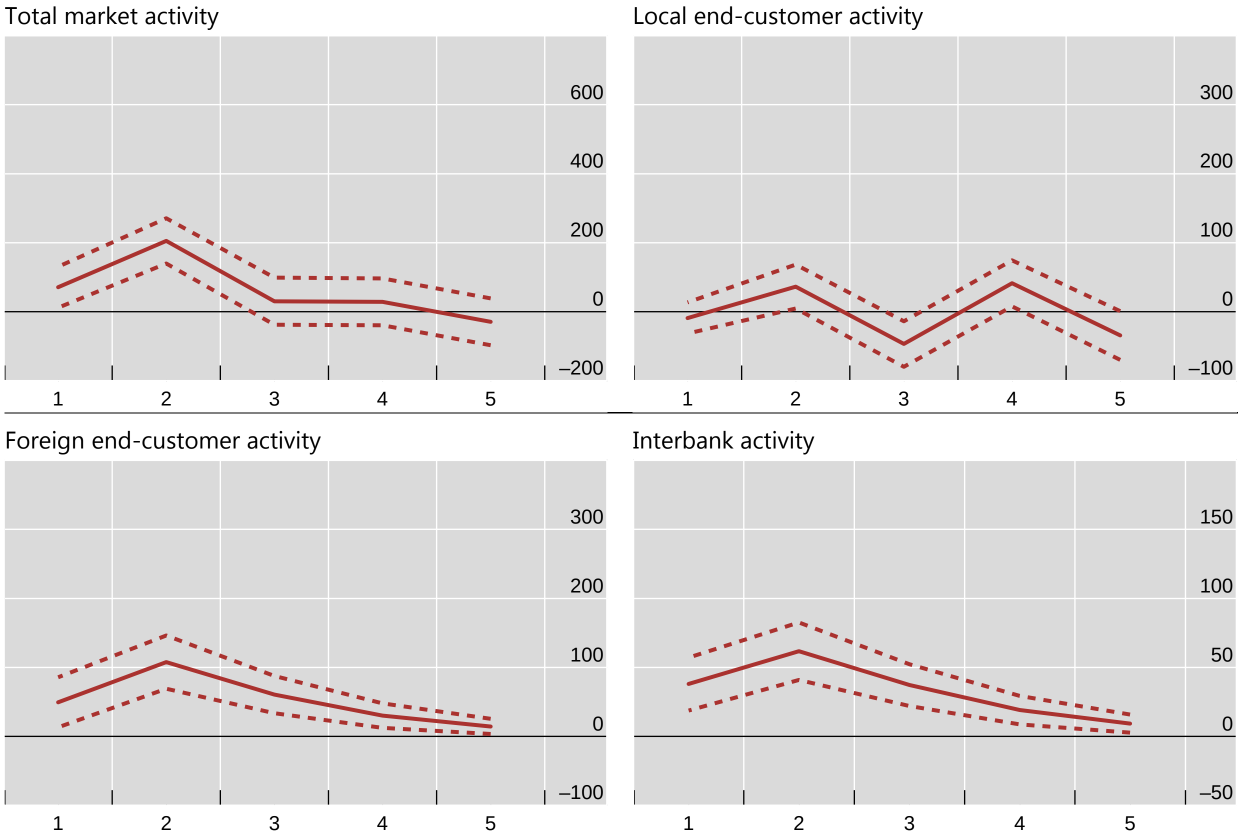
Impulse responses of trading volume to FX volatility when FX volatility is ordered last Graph B



The sample period is from 4 January 2010 to 18 March 2016. The local end-customer specification is estimated in first differences in light of the stationarity issue.

Source: authors' estimates.

Impulse responses of trading volume to FX volatility when FX volatility is ordered first Graph C



The sample period is from 4 January 2010 to 18 March 2016. The local end-customer specification is estimated in first differences in light of the stationarity issue.

Source: authors' estimates.

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