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Commonality in FX liquidity: High-frequency evidence☆

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ABSTRACT

We test the existence and reveal the main properties of commonality in liquidity for the foreign exchange (FX) markets at the high-frequency level. Accordingly, commonality in FX liquidity exists even at the high-frequency level and it has been gradually increasing over the last few years. Moreover, commonality increases significantly before (after) ECB (Fed) monetary policy announcements. Finally, commonality in FX liquidity has a significant positive impact on the commonality in FX return series, indicating that an increase in the intraday systematic liquidity risk might trigger a negative aggregate liquidity-return spiral in the FX markets.

1. Introduction

Liquidity, defined as the ability to trade large quantities of a security quickly with a little price impact, has been shown to be an essential element of financial markets. Even though earlier studies examined the aspects of liquidity from a single security perspective, we have experienced a growing body of literature recently that examines the co-movement between individual security liquidity and market-wide liquidity. Starting with the pioneering works by Chordia et al. (2000) and Hasbrouck and Seppi (2001), studies have found out that liquidity is subject to a contagion effect that effects other securities traded in the same market. Accordingly, liquidity is

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not just an input for market participants when deciding to trade a single security, but also a potential systemic risk factor due to its tendency to co-move across securities (Pastor and Stambaugh, 2003). Defined as *commonality* by Chordia et al. (2000), this co-movement property of liquidity and its potential sources are essential to understand in order to solve puzzles of market dry-ups and explain crashes, and further provide policy recommendations to resolve financial instabilities and more accurate guidance for portfolio selections. However, although the literature is exhaustive for equity and derivatives markets (Cenesizoglu and Grass, 2018; Sensoy, 2019; Tripathi et al., 2020; Benzennou et al., 2020), little research has been performed on the foreign exchange (FX) markets.[1]

Among those studies, Mancini et al. (2013) present one of the earliest evidence on liquidity commonality in the FX market. In contrast to the commonly held view that foreign exchange markets are liquid all the time, authors show that there are variations in currency liquidities and they occur simultaneously. Banti et al. (2012) develop a measure for liquidity and find that their global liquidity measure explains a fraction of liquidity fluctuations in individual currencies. Karnaukh et al. (2015) find that commonality in foreign exchange liquidity is strong (even stronger for developed market currencies) and there are episodes of systematic illiquidity within their sample period. Ranaldo and Santucci de Magistris (2019) provide a unified model for FX liquidity and volatility in a multi-currency environment. Accordingly, commonality in FX liquidity varies across currencies and time, and it can be explained by no-arbitrage rule.

As understood from above, systematic liquidity is critical for FX markets, arguably more critical than it is for other markets. However, the limitation of the number of studies due to unavailability of data leaves us with incomprehensive answers to important questions regarding commonality in FX liquidity, in particular at the high frequency level. For example, is commonality in FX liquidity present at high-frequency? If it does then at what level and does it change over time? How do the monetary policy announcements affect high-frequency FX liquidity commonality? How do commonality in liquidity and commonality in return interact with each other at the high-frequency level for the FX markets? To the best of our knowledge, these question remain unanswered and the topic requires further analysis.

In this study, we try to answer the abovementioned questions by analyzing the commonality in FX liquidity using a proprietary dataset of tick-by-tick FX quotations including 14 FX rates vis-a-vis US dollar for a sample period covering December 2015 to April 2018. Accordingly, we provide evidence for the existence of commonality in liquidity in the FX market at the high-frequency level that has been significantly increasing in recent years. Furthermore, Federal Open Market Committee (FOMC) meetings are found to have a direct effect on the high-frequency commonality in FX liquidity. Finally, commonality in FX liquidity is found to have a significant positive effect on the commonality in return series, suggesting that an increase in the intraday systematic liquidity risk might trigger a negative aggregate liquidity-return spiral in the FX markets.

2. Data and results

The data includes tick-by-tick bid and ask FX quotations stamped to Eastern Standard Time (EST), and is taken from Gain Capital, a US based dealer, with average monthly volume of 501.2 bn. USD and with over 140,000 traders worldwide, 1200 institutional partners. Our sample covers every trading day from December 15, 2014 to April 27, 2018. Data set covers a variety of exchange rates vis-a-vis US dollar, excluding pegged currencies, and including USDAUD, USDEUR, USDGBP, USDNZD, USDCAD, USDCHF, USDHUF, USDJPY, USDMXN, USDNOK, USDPLN, USDSEK, USDTRY and USDZAR.[2] These currencies account for approximately 76% of all daily trades in the foreign exchange market according to Bank for International Settlements (BIS)' latest triannual survey.[3]

Tick data is aggregated to 5-min interval data for each currency.[4] As the liquidity measure L, we use relative spread defined as last quoted spread over last mid price for each of the 5-minute intervals:

$$L = \frac{P_A - P_B}{(P_A + P_B)/2} \tag{1}$$

where P_A and P_B denote ask and bid quotations respectively.

[1] For example, Cenesizoglu and Grass (2018) and Sensoy (2019) both use intraday liquidity measures derived from order book of NYSE and Borsa Istanbul equity markets respectively, and show that commonality in liquidity exists for both sides of the order book, however it shows asymmetric properties with regard to ask- and bid-sides. Tripathi et al. (2020) examine commonality in liquidity for the Indian equity market. Their results suggest that commonality is time-varying and heterogeneous across conditional quantiles of liquidity. In a very recent work, Benzennou et al. (2020) investigate the liquidity commonality across European options and stock futures, and show that commonality is stronger for stock futures and options written on the same underlying asset.

[2] We use international standard abbreviations for the sample currency pairs. For the explanations of these abbreviations, see https://www.iban.com/currency-codes

[3] www.bis.org/statistics/rpfx19.htm

[4] We prefer 5-minute frequency sampling following the studies by Andersen et al. (2001) and Hansen and Lunde (2001) on intraday volatility analysis. Hansen and Lunde (2001) state that at 5-minute sampling, they find that the true confidence interval about the realized volatility (RV) can be as much as 100% larger than those based on an absence of microstructure noise assumption. Similarly, Andersen et al. (2001) argue that in order to analyze intraday volatiltiy dynamics, the literature suggests the desirability of sampling at very high frequencies, striving to match the ideal of continuously observed frictionless prices. However, the reality of market microstructure suggests not sampling too frequently due to potential microstructure noise. Both papers suggest that 5-min is a good sampling frequency.

2.1. Evidence of high-frequency commonality in FX liquidity

The first argument to be tested is that there is commonality in liquidity even at the high-frequency level. At this stage, we use the following benchmark model of Chordia et al. (2000):

$$\Delta L_{i,t} = \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} + \varepsilon_{i,t} \tag{2}$$

In this setup, the change in individual FX liquidity is estimated by taking the first difference, i.e.,

$$\Delta L_{i,t} = L_{i,t} - L_{i,t-1} \tag{3}$$

where $L_{i,t}$ is the measure of an individual liquidity for currency i, at time t, and $\Delta L_{M,i,t}$ is the equally-weighted cross sectional average of the change in liquidity variable for all currencies at time t, excluding currency i,

$$\Delta L_{M,i,t} = \sum_{j=1 j\neq i}^{14} \Delta L_{j,t} \tag{4}$$

The reason for excluding each currency when calculating market liquidity is to eliminate the effect of individual currency $i$âs own variation on the market average. In order to capture the effect of non-concurrent adjustments in liquidity variation at the currency and market level, the lag and lead variables for market liquidity are also included in the regression.

$R_{M,i,t}$ denotes the market return for currency i and calculated in a similar fashion to market liquidity, i.e.,

$$R_{M,i,t} = \sum_{j=1 j\neq i}^{14} \frac{P_{M,j,t} - P_{M,j,t-1}}{P_{M,j,t}} \tag{5}$$

where $P_{M,i,t} = (P_{A,i,t} + P_{B,i,t})/2$ is the mid-price for currency i at time t.[5]

Finally, $V_{i,t}$ is the volatility for currency i within the interval that covers $t-1$ to t and it is estimated via the Garman and Klass (1980) method:

$$V_{i,t} = \sqrt{0.5\left(\log\left(P^H_{M,i,t}\right) - \log\left(P^L_{M,i,t}\right)\right)^2 - (2\log(2) - 1)\left(\log\left(P^C_{M,i,t}\right) - \log\left(P^O_{M,i,t}\right)\right)^2} \tag{6}$$

where $P^H_{M,i,t}$, $P^L_{M,i,t}$, $P^C_{M,i,t}$ and $P^O_{M,i,t}$ denote the highest, lowest, closing and opening mid-price for the interval covering $t-1$ to t respectively.[6]

For each exchange rate, coefficient estimates of the model in Eq. (2) are provided in Panel A of Table 1. Accordingly, each individual FX liquidity depends on the market-wide liquidity. As expected, individual volatility has a positive and highly significant effect on the individual cost of trading. However, market return does not have a significant effect on the individual liquidity.

Following Chordia et al. (2000), we take the sum of β_1, β_2 and β_3 for each currency as the level of that currency's liquidity sensitivity to market-wide liquidity. Then we calculate the cross-sectional mean of these summed beta coefficients across currencies which is considered to represent the commonality in FX liquidity. According to Panel B of Table 1, we find that the average of $\beta_1 + \beta_2 + \beta_3$ terms across currencies is 0.037 and it is highly significant with a t-stat of 9.98, indicating a clear evidence of co-movement in FX liquidity at the high-frequency level.[7]

[5] Throughout this study, market-wide return and liquidity measures are estimated via equally-weighted scheme. For robustness, we also performed all our analyses with a volume-weighted market return and liquidity variables where the monthly volume data is obtained from BIS. Results are very similar qualitatively, therefore not reported here.

[6] We prefer Garman-Klass measure over RV for various reasons: First, to get a robust RV value, we need good amount of observations. In our work, we are using 5-minute intervals, therefore to create satisfactory number of observations within a 5-minute period, we need to consider very high frequency quotations. However, our data source is only one dealer, so in some of the cases (in particular for emerging market currencies) it is possible that quotations are not dynamic enough within a 5-minute interval. This might have a downward biased effect on RV due to many zero return observation within that 5-minute period. Second, in the paper by Martens and van Dijk (2007), authors argue that range based volatility approach is more efficient compared to realized return volatility. Third, range based volatility measures are subject to less microstructure noise as demonstrated by Alizadeh et al. (2002), and Brandt and Diebold (2006). There are also various references showing that one can use the price range information to improve volatility estimation. For example, see Yang and Zhang (2000), Alizadeh et al. (2002), Chou (2005), Brandt and Diebold (2006), Brandt and Jones (2006), and Martens and van Dijk (2007).

[7] We further repeated our analysis using daily data instead of 5-min intervals. Qualitatively, we obtained the same results, however the degree of commonality denoted by the cross-sectional average of the $\beta_1 + \beta_2 + \beta_3$ terms is much higher with a mean coefficient of 0.947 (and a t-stat of 34.92) in the case of daily data. A potential reason is that when we consider daily frequency, information in the market can be disseminated into FX quotations much better compared to a short-term period such as 5 min. Consequently, common reaction of various FX quotations depend stronger on the market information, thus leading to a higher degree of commonality.

Table 1
Liquidity sensitivity to the changes in market-wide FX liquidity **Panel A: Individual liquidity series**.

	$\Delta L_{M,i,t-1}$	$\Delta L_{M,i,t}$	$\Delta L_{M,i,t+1}$	$R_{M,i,t-1}$	$R_{M,i,t}$	$R_{M,i,t+1}$	$\Delta V_{i,t-1}$	$\Delta V_{i,t}$	$\Delta V_{i,t+1}$
AUD	−0.007***	0.040***	0.016***	0.003 **	−0.002	0.000	0.009***	0.035***	0.003**
	(−3.86)	(17.20)	(8.58)	(2.08)	(−1.62)	(0.36)	(5.48)	(20.26)	(2.11)
CAD	−0.017***	0.040***	0.014***	0.002	−0.006***	0.004***	0.009***	0.052***	0.002
	(−8.05)	(15.21)	(6.87)	(1.51)	(−3.74)	(2.60)	(4.95)	(26.50)	(0.95)
CHF	−0.008***	0.026***	0.013***	−0.003***	−0.001	0.001	0.002	0.024***	0.001
	(−6.48)	(16.26)	(10.40)	(−2.96)	(−0.62)	(1.30)	(1.64)	(19.79)	(0.60)
EUR	−0.023***	0.062***	0.025***	0.000	0.001	−0.001	0.004**	0.020***	0.000
	(−10.72)	(23.60)	(11.58)	(−0.05)	(0.92)	(−0.44)	(2.24)	(9.96)	(−0.07)
GBP	−0.007***	0.030***	0.015***	−0.001	−0.002	0.001	0.003***	0.032**	0.000
	(−4.29)	(14.99)	(9.58)	(−0.61)	(−1.44)	(0.55)	(2.31)	(20.95)	(−0.28)
HUF	−0.008***	0.020**	0.010**	0.002**	−0.001	0.001	0.002**	0.015***	0.002
	(−7.20)	(13.73)	(8.32)	(2.04)	(−1.04)	(0.75)	(2.31)	(13.45)	(1.87)
JPY	−0.007***	0.042***	0.024***	0.000	0.002	−0.002	0.006***	0.027***	0.004**
	(−3.27)	(17.05)	(11.86)	(0.28)	(1.02)	(−1.45)	(3.68)	(14.42)	(2.49)
MXN	−0.010***	0.036***	0.014***	−0.001	−0.001	0.000	−0.001	0.083***	0.009***
	(−5.00)	(15.30)	(7.11)	(−0.86)	(−0.60)	(−0.29)	(−0.76)	(46.62)	(5.44)
NOK	−0.015***	0.030***	0.012***	−0.001	0.000	−0.001	0.009***	0.047***	0.001
	(−11.64)	(18.93)	(9.05)	(−0.91)	(−0.05)	(−1.06)	(8.32)	(39.95)	(0.83)
NZD	−0.011***	0.027***	0.007***	0.002*	0.003**	−0.004***	0.011***	0.053***	0.006***
	(−6.47)	(12.70)	(4.03)	(1.66)	(2.01)	(−2.84)	(7.31)	(32.81)	(3.84)
PLN	−0.009***	0.023***	0.009***	−0.002	0.002	−0.001	0.005***	0.036***	0.001
	(−6.47)	(13.29)	(6.52)	(−1.51)	(1.55)	(−1.00)	(4.47)	(27.13)	(1.18)
SEK	−0.011***	0.035***	0.014***	0.000	−0.002**	0.001	0.008***	0.040***	0.003
	(−7.94)	(19.78)	(10.10)	(0.44)	(−2.29)	(0.66)	(6.78)	(30.24)	(2.12)
TRY	−0.009***	0.021***	0.007***	0.002*	−0.002*	0.001	−0.008***	0.056***	0.013***
	(−6.18)	(12.40)	(5.32)	(1.85)	(−1.86)	(0.79)	(−6.69)	(44.48)	(10.81)
ZAR	−0.007***	0.029***	0.016***	−0.002	−0.002	0.001	−0.003***	0.077***	0.015***
	(−4.37)	(14.26)	(9.79)	(−1.34)	(−1.32)	(1.07)	(−2.45)	(50.41)	(11.08)

Panel B: Testing for commonality at high-frequency: $\overline{\beta}_L$ t-stat 0.037*** 9.98 Note: In Panel A, for each exchange rate i, high frequency individual liquidity is regressed on average market-wide foreign exchange liquidity, market return and individual volatility: $\Delta L_{i,t} = \alpha + \beta_1 \Delta L_{M,i,t-1} + \beta_2 \Delta L_{M,i,t} + \beta_3 \Delta L_{M,i,t+1} + \beta_4 R_{M,i,t-1} + \beta_5 R_{M,i,t} + \beta_6 R_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} + \varepsilon_{i,t}$ The values in parentheses denote t-stats and they are obtained from Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. In Panel B, $\overline{\beta}_L$ denotes the currency cross-sectional average of the $\beta_1 + \beta_2 + \beta_3$. We test whether $\overline{\beta}_L$ is greater than zero or not. Null hypothesis is $\overline{\beta}_L = 0$. In both panels, *, ** and *** denote significance at 10%, 5% and 1% level respectively.

2.2. Time trend in high-frequency FX liquidity commonality

Another argument to be tested is whether there is a time trend in commonality in FX liquidity or not. To do so, we borrow the approach of Kamara et al. (2008) that is used on the US equity market and we estimate the main regression model in Eq. (2) for each trading day separately. For each day, the cross-sectional average of the sum of the coefficients of $\Delta L_{M,i,t-1}$, $\Delta L_{M,i,t}$, and $\Delta L_{M,i,t+1}$ (denoted by $\overline{\beta}_L$) is taken as an indicator of commonality in liquidity, in other words, systematic liquidity factor. Fig. 1 displays the time-varying commonality term $\overline{\beta}_L$ and it is clear that commonality has a tendency to increase with a gradual speed in recent years. Since the data shows wide fluctuations from time to time, a smoothed version (via Hodrick and Prescott, 1997 filter) is also presented in the same figure for a better understanding.

In order to statistically test the existence of a time variation, we consider two types of trends in commonality, namely (i) deterministic and (ii) stochastic, as in the work of Sensoy (2017). To examine the deterministic trend, we evaluate the regression in the following model:

$$\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 t + \varepsilon_t \tag{7}$$

whereas stochastic trend is evaluated under the model in the following equation:

$$\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 t + \alpha_2 \overline{\beta}_{L,t-1} + \varepsilon_t \tag{8}$$

Estimation results are provided in Table 2. According to this table, while there is a deterministic trend in liquidity commonality, we do not observe a significant stochastic trend. Significant positive time trend evidenced by high t-stats reveals that high-frequency systematic liquidity risk has been increasing in the last few years, making investors and policy makers more vulnerable to liquidity shocks in the FX markets.

One potential reason for this result might be the increased activity of algorithmic trading in global financial markets. In particular, increased capacity for reaching to public information and processing it faster makes algorithmic traders to respond to new information quickly in the same direction. This creates an aggregate pressure on the FX market liquidity, thus creating a higher commonality.

However, we also need to mention that a significant trend in commonality in FX liquidity is not necessarily bad, at least for certain

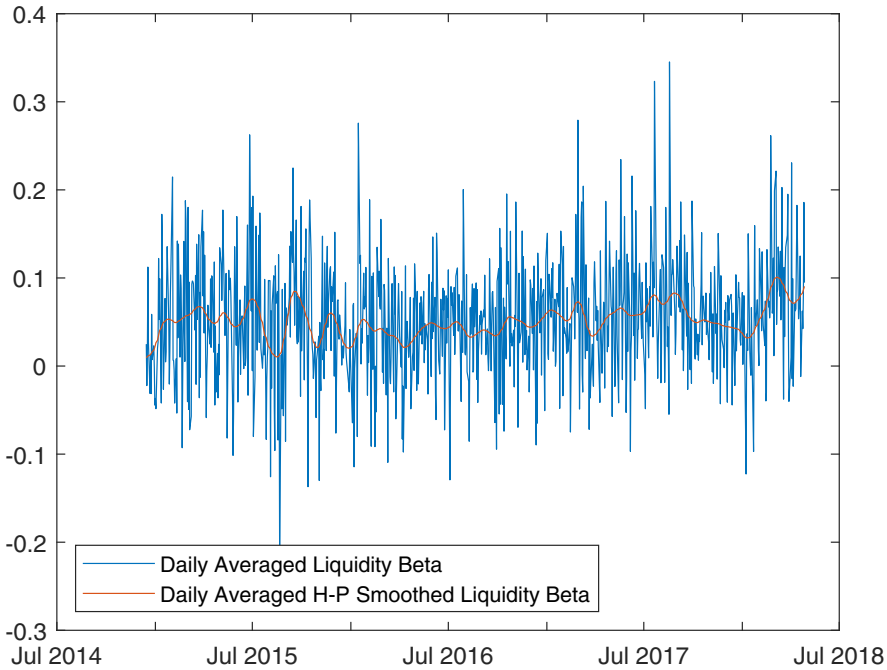

Fig. 1. Time-varying commonality in FX liquidity ($\overline{\beta}_L$).

Table 2
Trend in systematic liquidity Panel A: Deterministic trend.

	Estimate	t-stat
α_0	−0.160**	−2.46
t	0.003 ***	2.84
	Panel B: Stochastic trend	
	Estimate	**t-stat**
α_0	−0.165**	−2.44
$\boldsymbol{t}$	0.003***	2.82
$\overline{\beta}_{L,t-1}$	−0.006	−0.19

Note: $\overline{\beta}_L = \beta_1 + \beta_2 + \beta_3$ where β_1, β_1, β_1 are coefficients obtained from estimating Eq. (2) on a daily basis. Daily $\overline{\beta}_{L,t}$ series is tested for deterministic and stochastic trends by the equations $\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 t + \varepsilon_t$ and $\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 t + \alpha_2 \overline{\beta}_{L,t-1} + \varepsilon_t$ respectively. t-stats are obtained from Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

periods. For instance, during high global liquidity conditions such as potential future quantitative easing operations for any reason, it is likely to see an overall liquidity improvement for all sample foreign exchange rates, eventually reducing transaction costs and leading to increased trading activities.

2.3. Impact of monetary policy announcements on FX liquidity commonality at the high-frequency level

We further test whether monetary policy announcements affects the FX commonality in liquidity or not at the high-frequency level. At this stage, we limit ourselves with the announcements made by the FOMC and the European Central Bank (ECB) due to their relatively strong impact on world-wide monetary policy determination. During our sample period, there are 26 FOMC meetings and 27 ECB monetary policy meetings, and these meetings never overlap. In fact, there are always at least 5 days difference between ECB and FOMC meetings except only for December 2017, where the difference is 1 day. Using the time-varying liquidity commonality term $\overline{\beta}_{L,t}$ obtained in Section 2.2, we run the following model to assess the impact of monetary policy announcements on systematic liquidity while controlling for the trend in commonality.

$$\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 Dummy_{ECB} + \alpha_2 Dummy_{FOMC} + \alpha_3 t + \varepsilon_t \tag{9}$$

Here the FOMC (ECB) dummy variable takes the value 1 on the days when there is a monetary policy decision announcement by the FOMC (ECB) and zero otherwise.[8] The coefficient estimates of this equation are displayed in Table 3.

Results show that, FOMC announcements create a highly significant positive impact on commonality, increasing the high-frequency co-movement of liquidity in the FX market. On the other hand, even though the sign is positive, we don't observe such a significant impact of ECB monetary policy decisions. Results reveal the increased importance of the Fed's decisions on FX market participants, and stresses on the potential challenges to be faced with other central banks when one clearly dominates the others (Sensoy, 2016).[9]

Another interesting aspect of monetary policy announcements is their pre-announcement impact on commonality in addition to their post-announcement effect. Therefore, we expand our analysis to see if the commonality changes some periods before the monetary policy announcements. For this part, we perform an analysis similar to those of Morck et al. (2000) and Sensoy (2016). In particular, we average daily cross-sectional mean beta $\overline{\beta}_{L,t}$ first on only those trading days in the event windows that cover five trading days prior to the monetary policy announcements. Then we repeat the same procedure on whole days except those that belong to the event windows. The mean comparison of the whole sample and the event window is based on a one-tail, two-sample *t*-test for differences in means. Further, the t-statistics are corrected for unequal variances whenever appropriate using the Satterthwaite (1941) approximation. Accordingly, we find that for both central bank announcements, daily average beta is higher for event windows (ECB: 0.063 & Fed: 0.051) compared to non-event periods (ECB: 0.049 & Fed: 0.050). However, the difference is only significant in the case of ECB announcement. We believe that there are two potential explanations for this situation: i) an information leakage before ECB announcements, or ii) a better signalling & communication with regard to future monetary policy by the ECB so that market participants can position themselves better collectively prior to the ECB announcements. In fact, the latter argument is supported by the recent study of Bennani et al. (2020) where authors find that ECB communication related to conventional measures explain the future monetary policy well. Overall, we face with an interesting picture where commonality in FX liquidity significantly increases before ECB announcements and after Fed announcements.

2.4. High-frequency relation between systematic liquidity and systematic return risks

One aspect that would be of interest to market participants, policy makers and academics would be the interaction between commonality in liquidity and the common movements in exchange rate levels. This has been studied in detail by Brunnermeier and Pedersen (2008) for asset markets and it has been shown that in turbulent times, the situation evolves into a worsening return-liquidity spiral. Akyildirim et al. (2018) examine this concept for eurozone sovereign bond markets and show that commonality in bond liquidity has a strong impact on the commonality in yield changes, but not vice versa. Kamara et al. (2008) find that these two commonalities have common drivers in the US equity market. However, to the best of our knowledge, this concept has not been studied for the FX market in an empirical setup.

At this stage, we start by introducing a commonality measure for the changes in the exchange rate levels via a framework similar to what we have done for the liquidity. Inspired by our main model given by Eq. (2), we estimate the following model for each exchange rate i on a daily basis.

$$\begin{aligned} R_{i,t} &= \alpha + \beta_1 R_{M,i,t-1} + \beta_2 R_{M,i,t} + \beta_3 R_{M,i,t+1} + \beta_4 \Delta L_{M,i,t-1} + \\ &\beta_5 \Delta L_{M,i,t} + \beta_6 \Delta L_{M,i,t+1} + \beta_7 \Delta V_{i,t-1} + \beta_8 \Delta V_{i,t} + \beta_9 \Delta V_{i,t+1} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

For each day, the cross-sectional average of the β_1, β_2 and β_3 coefficients (denoted by $\overline{\beta}_R$) is taken as a proxy for the commonality in exchange rate levels, i.e., systematic return factor. Fig. 2 shows the daily commonality in return series for our sample period. For comparison purposes, we also display the Hodrick-Prescott filtered trend series for the commonality in both FX liquidity and return series in Fig. 3.

We first start with a trend analysis and estimate the systematic return counterparts of the models given in Eqs. (7) and (8). The results are provided in Table 4. Accordingly, we observe a significant negative trend in systematic return risk over the last few years.

Since we have found out that commonality in both liquidity and return series have significant time trends, we continue with performing an unrestricted vector autoregression (VAR) analysis on the daily changes of these variables to examine their interrelationship. According to Bayesian Information Criteria, optimal lag is found to be 3 and we estimate our model accordingly. The results are presented in Table 5.

Accordingly, we see that commonality in liquidity has a weak yet significant positive effect on commonality in return series. The explanatory power of 1 and 2 day lagged liquidity commonality terms shows us that an increase in the systematic FX liquidity risk most likely increases the systematic return risk in FX markets. However, we do not see a reverse relationship. This evidence is similar to that found by Akyildirim et al. (2018) for the eurozone sovereign bond markets, and it emphasizes the increased importance of liquidity

[8] Alternative variations of this dummy variable, such as taking the value 1 in the event windows of [−1,0] or [0,1], were also used. Results are similar qualitatively, therefore they are not reported here.

[9] Similar findings are also observed by recent papers. For example, Temesvary et al. (2018) show that changes in U.S. monetary policy affect U.S. banks' cross-border claims as much as the host country's monetary policy, a result in line with those of Avdjiev and Hale (2019). Moreover, Mackowiak (2007) shows that the price level and real output in a typical emerging market respond to U.S. monetary policy shocks by more than the price level and real output in the U.S. itself.

Table 3
Impact of monetary policy announcements on the commonality in FX liquidity.

	$Dummy_{ECB}$	$Dummy_{FOMC}$	t
Estimates	0.016	0.0383***	0.011**
t-stats	(1.28)	(2.91)	(2.28)

Note: This table reports the coefficient estimates of the following model: $\overline{\beta}_{L,t} = \alpha_0 + \alpha_1 Dummy_{ECB} + \alpha_2 Dummy_{FOMC} + \alpha_3 t + \varepsilon_t$ where $\overline{\beta}_{L,t}$ is the daily liquidity commonality term, $Dummy_{FOMC}$ (or $Dummy_{ECB}$) is a dummy variable that takes 1 on the day when the FOMC (or ECB) decision is announced. In the regression model, t-stats are obtained from Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

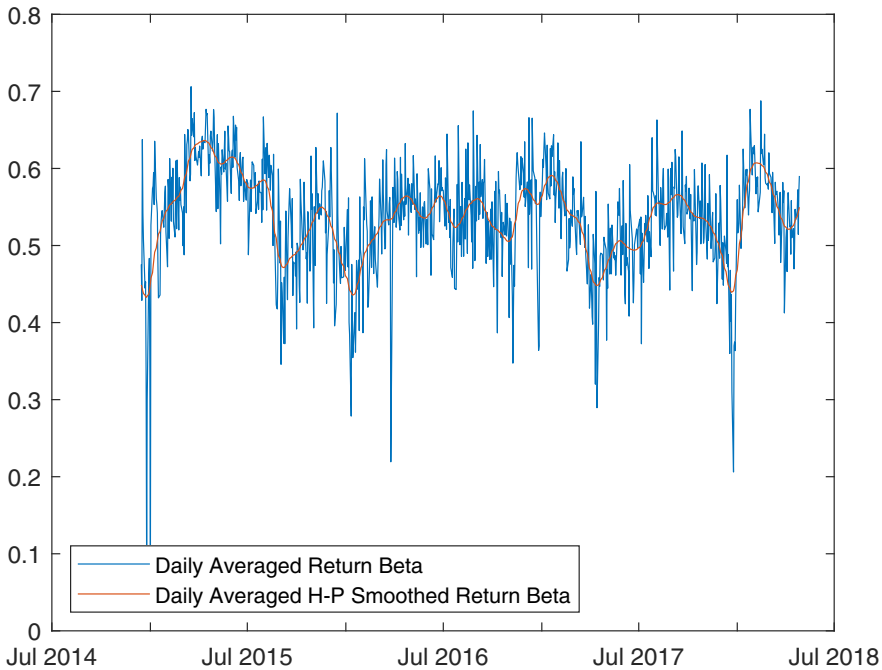

Fig. 2. Time-varying commonality in FX return ($\overline{\beta}_R$).

conditions in FX markets for financial stability in recent years, even at the high-frequency level.

3. Conclusion

Recent literature has shown us that liquidity is not only an attribute of a single asset, but there exists a significant common component that influences individual liquidity. We test this assertion for the foreign exchange markets, focusing on the commonality in FX liquidity at the high-frequency level.

Even though the degree of commonality is less compared to the case when we use daily data, we still find that high-frequency liquidity commonality exists in FX markets. Moreover, it has been gradually increasing over the last few years, making algorithmic traders and policy makers more vulnerable to intraday individual liquidity shocks in the FX markets. We show that, even controlling for the positive trend in commonality, Fed's monetary policy decisions have a significant positive impact on the high-frequency FX liquidity co-movement whereas ECB does not create such an effect. Results reveal the increased importance of the Fed's decisions on high-frequency trading activity in the FX markets, and stresses on the potential challenges to be faced by other central banks when one clearly dominates the others. However and interestingly, we observe a significant increase in commonality before ECB announcements whereas this is not the case for the announcements by Fed. We believe that this might be a sign of either information leakage prior to ECB announcements or a better signalling and communication policy by the ECB with regard to its future actions. Finally, we consider the bilateral relation between commonality in liquidity and commonality in return series in FX markets at the high-frequency level. We find that liquidity commonality has a positive explanatory power on return commonality, but not vice versa. This result points out to the increased importance of intraday liquidity conditions in FX markets for financial stability in recent years, especially with regards to cases like flash crashes.

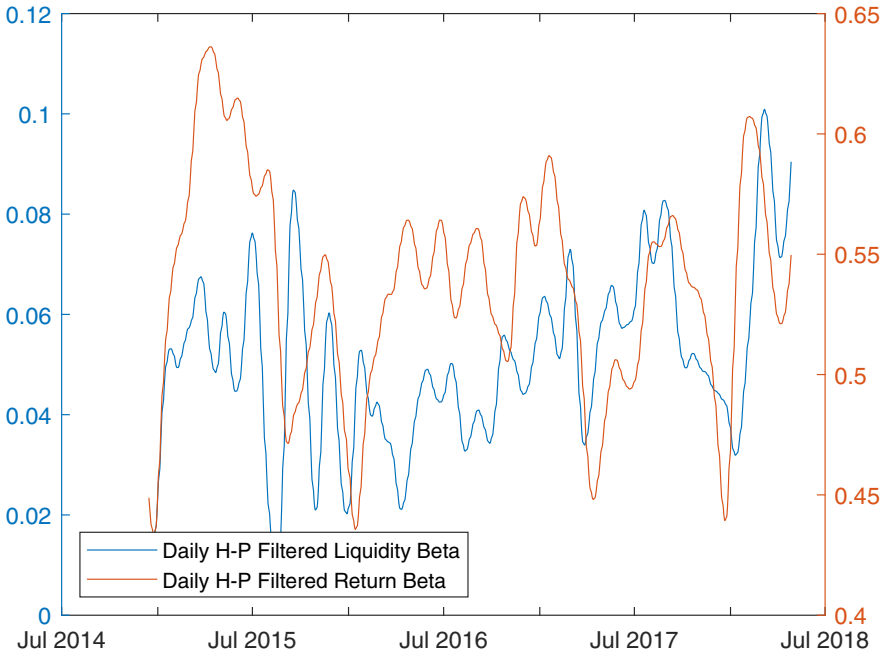

Fig. 3. Time-varying commonality in FX liquidity ($\overline{\beta}_L$) and FX return ($\overline{\beta}_R$). For a better understanding, series are filtered by Hodrick-Prescott procedure.

Table 4
Trend in systematic return.

Panel A: Deterministic trend	Estimate	t-stat
α	0.559***	127.56
t	−0.003***	−4.13
Panel B: Stochastic trend		
	Estimate	**t-stat**
α	0.273***	18.55
t	−0.002**	−2.22
$\overline{\beta}_{R,t-1}$	0.51***	19.61

Note: $\overline{\beta}_R = \beta_1 + \beta_2 + \beta_3$ where $\beta_1, \beta_1, \beta_1$ are coefficients obtained from estimating Eq. (10) on a daily basis. Daily $\overline{\beta}_R$ series is tested for deterministic and stochastic trends by the equations $\overline{\beta}_{R,t} = \alpha_0 + \alpha_1 t + \varepsilon_t$ and $\overline{\beta}_{R,t} = \alpha_0 + \alpha_1 t + \alpha_2 \overline{\beta}_{R,t-1} + \varepsilon_t$ respectively. t-stats are obtained from Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

Table 5
Parameter estimates for the unrestricted VAR(3) model using the daily changes in commonality in liquidity $\overline{\beta}_L$ and commonality in return $\overline{\beta}_R$ series.

	$\overline{\beta}_R$	t-stat	$\overline{\beta}_L$	t-stat
$\overline{\beta}_{L,-1}$	0.038*	(1.72)	2.610***	(> 10)
$\overline{\beta}_{L,-2}$	0.075*	(1.73)	−2.282***	(< − 10)
$\overline{\beta}_{L,-3}$	−0.030	(1.63)	0.664***	(> 10)
$\overline{\beta}_{R,-1}$	2.821***	(> 10)	0.015	(0.81)
$\overline{\beta}_{R,-2}$	−2.680***	(< − 10)	−0.025	(−0.66)
$\overline{\beta}_{R,-3}$	0.858***	(> 10)	0.011	(0.55)
Constant	0.000	(0.39)	0.000	(0.53)

Note: t-stats are obtained from Newey-West Heteroskedasticity and Autocorrelation Corrected (HAC) standard errors. *, ** and *** denote significance at 10%, 5% and 1% level respectively.

CRediT authorship contribution statement

Ahmet Sensoy: Conceptualization, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Sevcan Uzun:** Conceptualization, Methodology, Writing - original draft, Supervision, Data curation, Writing - review & editing. **Brian M. Lucey:** Conceptualization, Writing - original draft, Writing - review & editing, Supervision.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2020.101577

References

Akyildirim, E., Nguyen, D.K., Sensoy, A., 2018. A tale of two risks in the EMU sovereign debt markets. Econ. Lett. 172, 102–106.
Alizadeh, S., Brandt, M., Diebold, F., 2002. Range-based estimation of stochastic volatility models. J. Financ. 57, 1047–1091.
Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2001. The distribution of realized exchange rate volatility. J. Am. Stat. Assoc. 96, 42–55.
Avdjiev, S., Hale, G., 2019. U.S. monetary policy and fluctuations of international bank lending. J. Int. Money Financ. 95, 251–268.
Banti, C., Phylaktis, K., Sarno, L., 2012. Global liquidity risk in the foreign exchange market. J. Int. Money Financ. 31 (2), 267–291.
Bennani, H., Fanta, N., Gertler, P., Horvath, R., 2020. Does central bank communication signal future monetary policy in a (post)-crisis era? the case of the ECB. J. Int. Money Financ. 104, 102167.
Benzennou, B., ap Gwilym, O., Williams, G., 2020. Commonality in liquidity across options and stock futures markets. Financ. Res. Lett. 32, 101096.
Brandt, M., Diebold, F., 2006. A no-arbitrage approach to range-based estimation of return covariances and correlations. J. Bus. 79, 61–74.
Brandt, M., Jones, C., 2006. Volatility forecasting with range-based EGARCH models. J. Bus. Econ. Stat. 24, 470–486.
Brunnermeier, M.K., Pedersen, L.H., 2008. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.
Cenesizoglu, T., Grass, G., 2018. Bid- and ask-side liquidity in the NYSE limit order book. J. Financ. Markets 38, 14–38.
Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. J. Financ. Econ. 56, 3–28.
Chou, R., 2005. Forecasting financial volatilities with extreme values: the conditional autoregressive range (CARR) model. J. Money Credit Bank. 37, 561–582.
Garman, M.B., Klass, M.J., 1980. On the estimation of security price volatilities from historical data. J. Bus. 53, 67–78.
Hansen, P.R., Lunde, A., 2001. Realized variance and market microstructure noise. J. Bus. Econ. Stat. 24, 127–161.
Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows, and liquidity. J. Financ. Econ. 59, 383–411.
Hodrick, R.J., Prescott, E.C., 1997. Postwar US business cycles: an empirical investigation. J. Money Credit Bank. 29, 1–16.
Kamara, A., Lou, X., Sadka, R., 2008. The divergence of liquidity commonality in the cross-section of stocks. J. Financ. Econ. 89, 444–466.
Karnaukh, N., Ranaldo, A., Söderlind, P., 2015. Understanding FX liquidity. Rev. Financ. Stud. 28 (11), 3073–3108.
Mackowiak, B., 2007. External shocks, U.S. monetary policy and macroeconomic fluctuations in emerging markets. J. Monet. Econ. 54, 2512–2520.
Mancini, L., Ranaldo, A., Wrampelmeyer, J., 2013. Liquidity in the foreign exchange market: measurement, commonality, and risk premiums. J. Financ. 68 (5), 1805–1841.
Martens, M., van Dijk, D., 2007. Measuring volatility with the realized range. J. Econ. 138, 181–207.
Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? J. Financ. Econ. 58, 215–260.
Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 113, 642–685.
Ranaldo, A., Santucci de Magistris, P., 2019. Trading volume, illiquidity and commonalities in FX markets. University of St. Gallen.School of Finance Research Paper No. 2018/23
Satterthwaite, F.E., 1941. Synthesis of variance. Psychometrica 6, 309–316.
Sensoy, A., 2016. Commonality in liquidity: effects of monetary policy and macroeconomic announcements. Financ. Res. Lett. 16, 125–131.
Sensoy, A., 2017. Firm size, ownership structure, and systematic liquidity risk: the case of an emerging market. J. Financ. Stab. 31, 62–80.
Sensoy, A., 2019. Commonality in ask-side vs. bid-side liquidity. Financ. Res. Lett. 28, 198–207.
Temesvary, J., Ongena, S., Owen, A.L., 2018. A global lending channel unplugged? Does U.S. monetary policy affect cross-border and affiliate lending by global u.s. banks? J. Int. Econ. 112, 50–69.
Tripathi, A., Dixit, A., Vipul, V., 2020. Liquidity commonality in extreme quantiles: Indian evidence. Finance Research Letters 101448.(forthcoming)
Yang, D., Zhang, Q., 2000. Drift-independent volatility estimation based on high, low, open, and closing prices. J. Bus. 73, 477–491.