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Liquidity commonality in sovereign bond markets

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ABSTRACT

This paper documents commonality in the liquidity of sovereign bonds. We show that local market-level liquidity changes exert a substantial influence on the liquidity of single bonds. Unlike in equity markets there is only little evidence that changes in global liquidity affect the liquidity of individual sovereign bond markets. Instead, we document the occurrence of negative cross-market correlations of liquidity across several markets and time periods. The results further suggest that diverging monetary policy and the flight-to-safety phenomenon contribute to this decoupling in liquidity correlations.

1. Introduction

Sovereign bond markets are among the largest and most important financial markets in the world.[2] Apart from their size these markets are crucial for public sector financing (Fleming & Liu, 2016), monetary policy transmission (Taylor, 1995) and because sovereign bonds are frequently used as collateral in repo transactions (Nyborg, 2016). This paper fosters the understanding of common movements in liquidity in these markets and has implications for regulators, investors and academics.

Many crisis episodes such as the 1998 bond market crisis or the 1987 stock market crash have been characterized by a severe deterioration in market liquidity not coupled with any other noteworthy events (Chordia et al., 2000). Consistent with this observation researchers have documented the existence of common movements in liquidity (“commonality”) that can explain sudden dry ups of the liquidity of many securities or markets at the same time.[3] Apart from impacting the stability and resiliency of a market common (systematic) movements in liquidity suggest the existence of a priced liquidity risk factor (Acharya & Pedersen, 2005) and have implications for investors that want to hedge their portfolios against liquidity shocks.

This paper studies the existence and drivers of commonality in liquidity in sovereign bond markets using data from inter-dealer markets. Commonality in these markets is of particular interest because: First, liquidity depends largely on (common) public information (Fleming & Liu, 2016; Fleming & Remolona, 1999) suggesting a high degree of commonality within a market. Second, sovereign bond markets play a special role as safe havens during flight-to-safety scenarios (Beber et al., 2008) which suggests liquidity conditions diverge across markets and thus questions the existence of global commonality in this market as found for example by Brockman et al. (2009) for equities.

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[2] The total value of outstanding sovereign bonds is estimated to be about USD 11.0 trillion in the US and EUR 6.8 trillion in the euro area. The average daily trading volume in the US treasury markets in June 2014 was about USD 500 billion, compared to only USD 230 billion for NYSE stocks. See Fig. 5 for more details on historical numbers.

[3] The existence of commonality in liquidity has been found among US equities (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001), international equity markets (Brockman et al., 2009) and FX markets (Karnaukh et al., 2015; Mancini et al., 2013; Sensoy et al., 2021).

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In addition, trading in sovereign bond markets is usually facilitated by dealers as opposed to a limit order-book which allows additional insights to be gained on the effect of the market structure on commonality. Fabre and Frino (2004) suggest that commonality in liquidity is less important in dealer markets. Moreover, Sensoy (2019) finds that systematic liquidity risk might be dependent on order size and of a different nature for retail and institutional investors. From this perspective, studying an inter-dealer market is particularly interesting. While research in equity markets has found that commonality in liquidity is mostly driven by demand-side explanations such as correlated trading behavior of investors commonality in liquidity in sovereign bond markets is likely to be more dependent on dealer behavior and thus factors related to the supply of liquidity.[4]

By the virtue of studying commonality in liquidity this paper is related to studies that investigate the phenomenon for other asset classes. Commonality in liquidity was first documented for US equities (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001). These findings have been confirmed in international equity markets (Brockman et al., 2009; Karolyi et al., 2012). More recent studies have also detected the existence of global commonality across international equity markets (Brockman et al., 2009), FX markets (Karnaukh et al., 2015; Mancini et al., 2013; Sensoy et al., 2021) and commodity markets (Marshall et al., 2013). Furthermore, there are studies that relate liquidity across different asset markets such as the US corporate bond and CDS market (Pu, 2009) or the US equity and Treasury market (Chordia et al., 2005).

Besides documenting the existence of commonality in liquidity, several studies attempt to identify the drivers of common liquidity movements in the equity market. The most prominent explanation for commonality in liquidity include correlated trading behavior of investors (Kamara et al., 2008; Koch et al., 2016), funding constraints (Brunnermeier & Pedersen, 2008; Gârleanu & Pedersen, 2007; Kyle & Xiong, 2001), liquidity pullback (Nyborg & Östberg, 2014), macroeconomic announcements (Brockman et al., 2009), same market makers (Coughenour & Saad, 2004) and cultural and behavioral factors (Moshirian et al., 2017).

The literature that studies liquidity in bond markets has so far focused on the characterization of liquidity in bond markets in general (Cheung et al., 2005; Fleming, 2003), the recent crisis (Dick-Nielsen et al., 2012), the term structure of liquidity (Goyenko et al., 2011) and the pricing of liquidity (Amihud & Mendelson, 1991; Bao et al., 2011; Chen et al., 2007; Favero et al., 2010; Friewald et al., 2012). Li et al. (2009) studies liquidity risk arising from the common movements of returns and liquidity. None of these papers focuses extensively on commonality in liquidity nevertheless some of them contain indicative results. Fleming (2003) shows that liquidity is correlated across benchmark bonds. Similarly, Goyenko et al. (2011) show lead lag relationships between the liquidity of different bond market segments.

Given the importance of the economic phenomenon of commonality in liquidity as well as the size of the sovereign bond markets and their many special features a special analysis of commonality in liquidity in this market is merited. An analysis of the drivers of commonality in liquidity in these markets will yield important insights about the relative importance of supply and demand side factors in a dealer market. Moreover, this paper investigates whether global commonality (as found in FX or equity markets) generalizes to international sovereign bond markets. Given the save haven attributes of some markets and different monetary policy across countries phases with liquidity divergence are possible.

2. Data and liquidity proxy

Our analysis focuses on sovereign bond markets covered by MTS and Treasury CRSP. MTS is the largest European inter-dealer trading platform and the data set covers the following 11 Euro area countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), the Netherlands (NL) and Portugal (PT) over the entire sample period between 04/2003 and 12/2014.[5] Additionally, it has reasonable coverage in the Czech Republic (CZ), Poland (PL), Denmark (DK) and Israel (IL) but for shorter time periods.[6] We enrich this data with information from the US Treasury market (Treasury CRSP).[7] We are interested in sovereign bond markets in their entirety, which is why we consider a broad set of sovereign bonds across all maturities, which is consistent with other studies that research liquidity in bond markets such as Chen et al. (2007) or Li et al. (2009).

The MTS data contains all the quotes and trades with millisecond timestamps. The Treasury CRSP contains daily snap shots of bid and ask prices that are provided by ICAP or GovPX.[8] Furthermore, we use this data to calculate daily continuously compounded mid-price returns and volatility proxies (the calculation and use of these variables is explained in detail in Section 3 (baseline estimates) and 4.2 (robustness checks)). To avoid outliers, influencing the results, we winsorize variables at the 1% and 99% quantile.

We enrich the sample with aggregate economic quantities from Datastream and Refinitiv such as exchange rates, sentiment indices, gold prices, prime broker returns, local bank returns, the short rate, stock market returns and government bond yields (see Table A.1 for details).[9] Since we will run time series regressions at the bond-level we also remove all the bonds that have a time series of less than 50 days or no variation in bid–ask spreads over the entire sample period. Together this results in a final sample

[4] Karolyi et al. (2012): "Our evidence is more reliably consistent with demand-side explanations and challenges the ability of the funding liquidity hypothesis to help us understand important aspects of financial market liquidity around the world".

[5] A more detailed description of the MTS data set and the market microstructure of the MTS platform can be found in Östberg and Richter (2017).

[6] Start dates of data: Czech Republic 07/2011, Poland 12/2005, Denmark 11/2003, Israel 06/2009.

[7] This data does not include Japan and the UK the second and third largest bond markets according to the BIS debt securities statistics (https://www.bis.org/statistics/secstats.htm). For robustness analysis we analyze these markets based on Bloomberg data. See Section 4.1 for details.

[8] The CRSP DAILY US TREASURY DATABASE GUIDE (version of August, 2010) states: "From October, 1996 through January 2009, prices were supplied by GovPX, Inc. ICAP began providing data in February 2009".

[9] We apply a set of screens to the MTS data as explained in Östberg and Richter (2017).

Table 1
Descriptive statistics sample. Panel A contains information about the data source, which is either MTS or the Treasury CRSP Database (CRSP). It also contains information on whether intraday data is available (HF) or whether one has to rely on daily data (LF). Moreover, the table shows the start (Start) and end date (End) of the coverage in the sample. Panel B contains the overall number of bonds used for the analysis (#Bonds), the number of bond days in the sample (#Days), the average number of bonds observed on the average day (avg. # Bonds), the number of days the average bonds are in the sample (avg. # Days) as well as the number of the total bond-day observations (Bond-Day obs.). The table includes the following countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), the United States, (US), Denmark (DK), the Czech Republic (CZ), Poland (PL) and Israel (IL).

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	US	DK	CZ	PL	IL
Panel A: Data source and coverage																
Data	MTS	MTS	MTS	MTS	MTS	MTS	MTS	MTS	MTS	MTS	MTS	CRSP	MTS	MTS	MTS	MTS
Frequency	HF	HF	HF	HF	HF	HF	HF	HF	HF	HF	HF	LF	HF	HF	HF	HF
Start	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–04	2003–11	2011–07	2005–12	2009-06
End	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014–12	2014-12
Panel B: Number of observations																
# Bonds	32	236	371	257	24	458	74	34	474	204	112	613	53	25	43	18
# Days	2982	2982	2982	2982	2982	2982	2627	2982	2982	2982	2982	2942	2819	875	2246	1052
avg. # Bonds	15.6	43.5	62.1	58.2	9.5	80.8	19.4	8.4	69.7	26.5	19.2	191.8	11.8	17.2	15.2	8.1
avg. # Days	1452.8	550.2	498.8	675.3	1181.8	526.3	689.3	733.5	438.7	387.6	511.6	920.4	628.6	602.4	791.6	470.6
Bond-Day obs.	46.5	129.8	185.0	173.6	28.4	241.0	51.0	24.9	208.0	79.1	57.3	564.2	33.3	15.1	34.0	8.5

of 3028 securities. Table 1 contains detailed information about the sample. For the single countries we have between 18 (Israel) and 613 (France) sovereign bonds that we can use for our analysis. On average our sample covers between 8.1 (Israel) and 191.8 (USA) bonds at each point in time. Overall we use approximately 1.9 million bond days to estimate our models.

The paper of Langedijk et al. (2018) considers the bid–ask spread as a high-frequency liquidity benchmark and assesses whether low frequency liquidity measures can be applied in sovereign bond markets instead. Generally, the authors conclude that in sovereign bond markets high frequency liquidity measures should be preferred because low-frequency liquidity measures do not always work well in particular when the aggregation period is long. As a result of this we use high-frequency data, if possible (this is the case for markets with MTS data coverage).

In line with the recommendations in Langedijk et al. (2018) we calculate the bid–ask spread as the difference between the best ask price (P^A) and the best bid price (P^B) divided by the mid-price P^M at each quote update (n) for a given bond i at day t. We then calculate the equally weighted average across all quote updates for a bond $N_{i,t}$ as:

$$LIQUIDITY_{i,t} = \frac{1}{N_{i,t}} \sum_{n=1}^{N_{i,t}} \frac{P^A_{i,t,n} - P^B_{i,t,n}}{P^M_{i,t,n}}. \tag{1}$$

For the US market where no intraday liquidity information is available, we are forced to use low-frequency liquidity measures. As pointed out by Langedijk et al. (2018) this might be problematic due to information loss when aggregating and the resulting low correlations with high-frequency liquidity benchmarks. However, we alleviate potential concerns by choosing the best performing liquidity measure according to Langedijk et al. (2018) the end of day bid–ask spread (bid ask spread snapshots at the market close) and avoiding aggregation over long periods. The low frequency liquidity proxy is used for the US market, where no intraday data is available.[10]

3. Empirical analysis

3.1. Local commonality

To assess the degree of commonality in liquidity in sovereign bond markets we adopt the approach of Chordia et al. (2000). In this model the change in liquidity of an individual security is explained by the change in market liquidity. The idea is that if the change in the liquidity of a single sovereign bond can be explained by the change of the market liquidity, there is a common liquidity factor. We estimate the following time series regression for each sovereign bond in the sample:

$$\begin{aligned} \Delta LIQUIDITY_{B,t} = {} & \alpha + \beta_1 \Delta LIQUIDITY_{M,t} + \beta_2 \Delta LIQUIDITY_{M,t+1} \\ & + \beta_3 \Delta LIQUIDITY_{M,t-1} + \delta_1 RETURN_{M,t} + \delta_2 RETURN_{M,t+1} \\ & + \delta_3 RETURN_{M,t-1} + \delta_4 \Delta VOLATILITY_{B,t} + \epsilon_{B,t} \end{aligned} \tag{2}$$

[10] Moreover, the low frequency liquidity proxy is used for the calculations regarding the UK and Japanese markets in the robustness section.

Table 2
Descriptive statistics commonality. The table shows the mean and the standard deviation for the market liquidity ($LIQUIDITY_M$), the first difference of the market liquidity ($\Delta LIQUIDITY_M$), the market return ($RETURN_M$) and the average standard deviation ($VOLATILTIY_M$) for the 16 markets covered over the entire sample period at a daily frequency. The liquidity proxy used is the bid–ask spread calculated either from daily snap shots at close sourced from Treasury CRSP (US) or calculated from all intraday quote updates (all other countries) on the MTS platform. The returns are calculated from mid prices at close as log-returns. The standard deviation is calculated from intraday mid prices. These values are aggregated to market aggregates by calculating the equally weighted average.

	$LIQUIDITY_M$		$\Delta LIQUIDITY_M$		$RETURN_M$		$VOLATILITY_M$	
	mean	*sd*	*mean*	*sd*	*mean*	*sd*	*mean*	*sd*
AT	0.306	0.348	0.023	0.104	0.006	0.250	0.011	0.008
BE	0.206	0.220	0.004	0.073	0.010	0.184	0.012	0.007
DE	0.096	0.067	0.008	0.020	0.004	0.170	0.006	0.003
ES	0.623	0.633	0.010	0.172	0.011	0.300	0.025	0.021
FI	0.132	0.141	0.007	0.055	0.004	0.204	0.007	0.005
FR	0.357	0.276	0.017	0.067	0.011	0.208	0.016	0.006
GR	2.891	5.417	0.147	2.472	−0.070	1.315	0.095	0.209
IE	1.040	1.722	0.008	0.651	0.005	0.385	0.054	0.111
IT	0.155	0.191	0.004	0.061	0.004	0.192	0.008	0.008
NL	0.083	0.065	0.010	0.028	0.004	0.157	0.007	0.005
PT	1.226	2.204	0.006	0.620	0.001	0.402	0.057	0.109
US	0.035	0.003	0.000	0.001	0.000	0.252	0.212	0.159
DK	0.130	0.110	0.004	0.042	0.005	0.184	0.008	0.004
CZ	0.490	0.267	−0.075	0.107	0.011	0.142	0.033	0.025
PL	0.470	0.504	0.006	0.515	0.011	0.145	0.037	0.038
IL	0.171	0.066	−0.024	0.026	0.027	0.202	0.011	0.011

where $\Delta LIQUIDITY_{B,t}$ is the first difference of the liquidity levels of sovereign bond B at day t. As explained in Section 2, we use the bid–ask spread as liquidity measure either calculated from snap shots (US) or intraday quote updates (all other countries).[11] We calculate changes in market liquidity $\Delta LIQUIDITY_{M,t}$ as the equally weighted average of all the liquidity changes of the individual securities within a market (e.g. Italy or Germany). When calculating this average, we exclude the sovereign bond whose liquidity changes are the dependent variable.[12]

The market return $RETURN_{M,t}$ is calculated as the equally weighted average of the continuous mid-price return of the individual sovereign bonds in a country. Again, the return of the sovereign bond, whose liquidity is explained by the model, is excluded. This variable is added to the model to remove spurious dependence arising from an association between returns and the liquidity measure (see Chordia et al., 2000). Additionally, leads and lags of these variable are included to capture non-synchronous trading.[13]

The price volatility is calculated as the standard deviation of intraday mid-price returns (MTS sample) or the squared daily return (US). As pointed out in Molnár (2012) the most natural measure for how much asset prices change is the variance of returns. He also notes that daily volatility estimates from high-frequency data are precise. We therefore calculate volatility as the standard deviation of intraday mid-price returns if intraday data is available.

For some markets (e.g., the US) only close prices are available (in the data set in use). Molnár (2012) points out that in such cases the only estimate available is the squared daily return. The variable $\Delta VOLATILITY_{B,t}$ used in the regression is simply the first difference. Volatility is added to the regression as control variable because it is known to influence spreads (see e.g., Glosten & Milgrom, 1985). However, the are many other good choices of volatility proxies. To show that our results are not sensitive to the use of another volatility proxy we re-estimate our models with an alternative proxy in the robustness section. As mentioned in Section 2, to prevent outliers from influencing our results we winsorize variables at the 1% and 99% quantile.

Table 2 contains descriptive statistics for the aggregate time series for the variables used in this analysis for each of the countries. Fig. 1 plots these variables for the German market. The statistics show that the US, Dutch and German markets are by far the most liquid with average bid–ask spreads below 10 bps. In Italy spreads average at around 0.15%. Greece, Portugal, and Ireland show the highest bid–ask spreads with values above 1%. The first differences of the bid–ask spread are close to zero but usually slightly positive indicating an increase in bid–ask spreads over the sample period which is consistent with the stylized fact that liquidity has not recovered from the crisis (see, e.g., Bessembinder et al., 2018). Price returns are slightly positive (except for Greece) which is consistent with rising prices as a response to the low interest rate environment in the last years of the sample. The statistics for the standard deviation show that there is ample time series variation in liquidity in sovereign bond markets that we can exploit in our analysis.

[11] We analyze innovations in liquidity in line with the majority of the previous literature. Chordia et al. (2000) argue that innovations are less likely to be plagued with econometric problems arising from the presence of unit roots or serial correlation. However, this has been criticized by Hasbrouck and Seppi (2001) because they could not find unit roots. Innovations in liquidity in previous studies are either calculated as first differences, proportional changes or residuals from an auto-regressive regression. In this study (as described above) we use first differences. However, results with proportional changes are qualitatively similar (available upon request).

[12] As noted by Chordia et al. (2000) this removes the constraint that the average of all β coefficients needs to be unity.

[13] The use of the mid-price return is common in the fixed income literature. Examples include Cheung et al. (2005) and Li et al. (2009). However, this return should only be seen as a price change and not the total return of the sovereign bond.

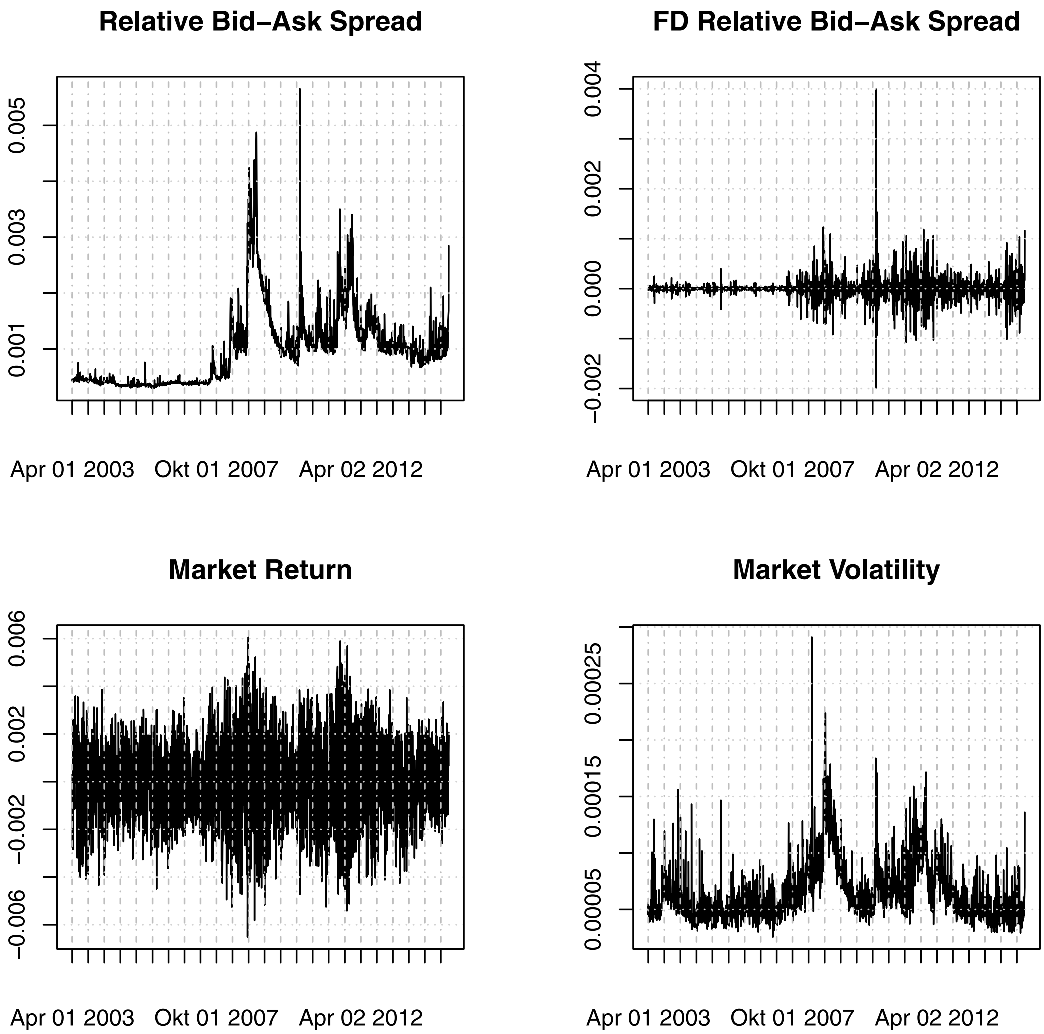

Fig. 1. Time series of liquidity, returns and volatility. This figure shows the relative quoted bid–ask spread for the German market (top left graph), the first difference in the relative quoted bid–ask spread for the German market (top right graph), the market return calculated from mid prices at close for the German market (bottom left graph) and the market volatility calculated as the standard deviation of intraday mid-price returns for the German market (bottom right graph). The graphs span the entire sample period from 04/2003–12/2014 and display values at the daily level.

Table 3 contains the result of estimating Eq. (2) for each security over the whole sample period summarized for each market. The first four rows report the average β_1 coefficient, the associated t-statistic (in parenthesis), the number of positive coefficients as well as the number of positive significant coefficients.[14] Rows 5–8 and 9–12 contain the same statistics for the β_2 and the β_3 coefficients. Row thirteen shows the average sum of the coefficients associated with the contemporaneous, lead and lag changes in market liquidity $SUM = \beta_1 + \beta_2 + \beta_3$. Row fifteen shows the median of this sum (associated p-values are based on a sign test). The last two columns contain the average adjusted R^2 and the additional adjusted R^2 that comes only from the explanatory power of market liquidity.[15]

The primary variable of interest is the contemporaneous coefficient (the β_1 coefficient) on $\Delta LIQUIDITY_{M,t}$. A positive and significant coefficient would mean that market-level liquidity changes can explain individual sovereign bond liquidity. The results in Table 3 show that the average β_1 coefficient associated with contemporaneous liquidity is quite large and positive for all the countries. The coefficients range from 0.32 (Denmark) to 0.82 (Czech Republic) with a cross-country average of 0.53. The mean β_1

[14] The t-test is based on the cross-sectional variation across all the estimated regression coefficients within a country. The percentage of positive and significant coefficients is based on the t-statistic associated with the regression coefficient in the single time series regression, which has been estimated using the method of Newey and West (1987) and is based on an assessment of significance at the 10% level.

[15] The latter is obtained by estimating the regression in Eq. (2) first without and then with the market liquidity variables and subtracting the resulting adjusted R^2 measures.

Table 3

Commonality in liquidity. This table contains the result of estimating time series regressions that relate the changes in liquidity of an individual security ($\Delta LIQUIDITY_B$) to the changes in liquidity of the market $\Delta LIQUIDITY_M$ while controlling for market returns $RETURN_M$ and changes in volatility ($\Delta VOLATILITY_B$) for each security over the whole sample period using daily data (t). We estimate for each bond B:

$$\Delta LIQUIDITY_{B,t} = \alpha + \beta_1 \Delta LIQUIDITY_{M,t} + \beta_2 \Delta LIQUIDITY_{M,t+1} + \beta_3 \Delta LIQUIDITY_{M,t-1}$$
$$+\delta_1 RETURN_{M,t} + \delta_2 RETURN_{M,t+1} + \delta_3 RETURN_{M,t-1} + \delta_4 \Delta VOLATILITY_{B,t} + \epsilon_{B,t}.$$

The first four rows in the table below report the average β_1 coefficient, the associated t-statistic (in parenthesis), the% of positive coefficients as well as the % of positive significant coefficients. The t-test is based on the cross-sectional variation across all the estimated regression coefficients within a country. The percentage of positive and significant coefficients is based on the t-statistic associated with the regression coefficient in the single time series regression which has been estimated using the method of Newey and West (1987) - assessment of significance at the 10% level. Rows 5–8 and 9–12 contain the same statistics for the β_2 and the β_3 coefficients (lead and lag). Row thirteen shows the average sum of the coefficients $SUM = \beta_1 + \beta_2 + \beta_3$. Row fifteen shows the median of this sum (associated p-values are based on a sign test). The last two rows contain the adjusted R^2 for the entire regressions as well as the part that comes from the addition of the market liquidity variables (contemporaneous, lead and lag). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), the United States, (US), Denmark (DK), the Czech Republic (CZ), Poland (PL) and Israel (IL).

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	US	DK	CZ	PL	IL
β_1	0.69***	0.35***	0.55***	0.58***	0.81***	0.45***	0.62***	0.38***	0.43***	0.30***	0.33***	0.59***	0.32***	0.82***	0.56***	0.55***
	(10.67)	(9.54)	(17.33)	(6.63)	(7.49)	(11.47)	(11.45)	(4.96)	(15.99)	(9.08)	(6.98)	(19.03)	(5.39)	(8.89)	(8.56)	(7.36)
% positive	100.0%	93.6%	96.0%	94.6%	100.0%	87.1%	86.5%	88.2%	97.9%	93.6%	91.1%	71.6%	88.5%	100.0%	100.0%	100.0%
% positive *	93.8%	67.4%	77.1%	65.8%	91.7%	49.3%	70.3%	58.8%	75.1%	63.2%	50.9%	52.2%	57.7%	100.0%	81.4%	100.0%
β_2	0.04	0.03***	0.03**	0.052*	0.03	−0.01	0.00	0.00	0.03***	0.02***	−0.02	0.01	0.01	0.04	0.04	0.04
	(1.37)	(5.06)	(2.56)	(1.90)	(1.59)	(−1.26)	(−0.16)	(0.17)	(3.63)	(4.41)	(−1.50)	(0.50)	(0.95)	(0.98)	(0.90)	(0.94)
% positive	68.8%	69.1%	58.8%	59.9%	75.0%	58.1%	48.6%	58.8%	62.0%	71.1%	40.2%	49.4%	50.0%	60.0%	53.5%	44.4%
% positive *	25.0%	19.9%	14.8%	11.3%	20.8%	9.6%	2.7%	5.9%	19.0%	23.5%	8.9%	10.4%	5.8%	16.0%	7.0%	16.7%
β_3	0.02**	0.01	0.02*	0.05*	0.03**	0.00	0.02	0.00	0.01	0.00	−0.02**	0.06***	−0.01	0.03	0.09	0.01
	(2.24)	(0.96)	(1.74)	(1.72)	(2.11)	(−0.42)	(0.74)	(−0.65)	(1.51)	(−0.10)	(−2.03)	(3.40)	(−1.43)	(0.65)	(0.87)	(0.22)
% positive	65.6%	61.0%	59.3%	52.1%	75.0%	54.8%	51.4%	47.1%	54.4%	55.9%	34.8%	50.9%	55.8%	56.0%	48.8%	61.1%
% positive *	25.0%	11.4%	9.7%	10.9%	16.7%	12.4%	6.8%	5.9%	8.9%	12.3%	6.2%	5.4%	9.6%	0.0%	2.3%	11.1%
SUM	0.76***	0.39***	0.59***	0.68***	0.87***	0.44***	0.64***	0.38***	0.47***	0.33***	0.29***	0.66***	0.32***	0.89***	0.69***	0.59***
	(9.76)	(10.15)	(17.58)	(5.15)	(8.37)	(12.09)	(10.66)	(4.95)	(14.88)	(9.40)	(6.25)	(14.47)	(5.33)	(7.16)	(3.63)	(6.07)
Median	0.82***	0.12***	0.44***	0.38***	0.87***	0.13***	0.67***	0.09***	0.23***	0.11***	0.08***	0.50***	0.08***	0.82***	0.58***	0.64***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2 add	0.182	0.079	0.074	0.101	0.206	0.063	0.249	0.209	0.133	0.072	0.089	0.016	0.1	0.147	0.115	0.066
R^2 mean	0.294	0.258	0.259	0.262	0.318	0.225	0.294	0.354	0.298	0.376	0.454	0.109	0.167	0.235	0.282	0.081
N	32	236	371	257	24	458	74	34	474	204	112	613	52	25	43	18

coefficient is also not a product of outliers. In the vast majority of the single regressions the β_1 coefficient is positive and significantly different from zero. The β_2 and β_3 coefficients are generally very small and often not significantly different from zero. The value of the sum of the coefficient ($\beta_1 + \beta_2 + \beta_3$) are usually very close to the mean β_1.

As outlined by Brockman et al. (2009) and Karolyi et al. (2012), the adjusted R^2 added by the market liquidity is another important statistic since it is less subject to scaling effects. The average R^2 ranges from 0.081 (Israel) to 0.454 (Portugal). The average added R^2 is 0.119. Since the R^2 is comparable across markets and across asset classes, this also allows a comparison of our results with the ones obtained for equity markets. The average R^2s reported here for sovereign bond markets are substantially higher than the ones reported in Brockman et al. (2009) (0.046) and Chordia et al. (2000) (0.017). This evidence suggests that commonality in liquidity exists among sovereign bonds and that it is even more pronounced than for equities.[16]

The previously presented results were obtained with the methodology used in Brockman et al. (2009) and Chordia et al. (2000). However, for bond markets this methodology has the problem that the securities analyzed have finite and different maturities. This creates two problems for the approach used above: (1) short-term bonds have higher weights and (2) sovereign debt and therefore also issuance activity of sovereign bonds is changing over time leading to clustering of observations in certain periods. In order to overcome this issue, we estimate the regressions quarterly for each bond. This mitigates the under-weighting of bonds with long maturity. Table 4 Panel A contains the average quarterly beta coefficients. We assess significance using two-way clustered standard errors (clustered around both bonds and time) generated from an intercept only regression.

To take the fact that observations cluster in time (mainly towards the end of the sample period) into account, we apply the Fama and MacBeth (1973) method. This means we calculate an average beta (from all bonds) for each quarter. Using the time series of quarterly (average) betas we test whether the time series average (of these betas) is statistically different from zero. To take into account autocorrelation across quarters we correct the standard errors using the method of Newey and West (1987). The classic Chordia et al. (2000) approach has problems with cross-equation correlation. This issue is solved in this setting due to the design of the Fama and MacBeth (1973) approach because it only considers one observation at each point in time.

The results in Table 4 obtained using the approaches described above confirm the results of the previously estimated basic model. The β_1 coefficient is still significantly positive in all the countries. In terms of magnitude the coefficients have increased

16 Note that R^2 calculated in Brockman et al. (2009) and Chordia et al. (2000) are R^2s produced by all the variables in the Eq. (5) while our additional R^2 only displays the additional explanatory power of the market liquidity variables. Thus, we compare a conservative estimate to an upper bound estimate.

Table 4
Commonality in liquidity — Quarterly Regressions. Panel A of this table contains the results of estimating Eq. (2) for each bond and quarter and then calculates the average coefficients from all bonds and quarters (pooled). Standard errors are calculated using intercept only regressions with standard errors clustered around both time and bonds (two-way clustering). The results in Panel B are calculated using the Fama and MacBeth (1973) approach. This is operationalized as follows: (1) in each quarter we estimate Eq. (2) for each bond, (2) we take the average across all bonds for each quarter and (3) we calculate the average across all quarters. Standard errors are calculated from all quarterly observations and are corrected for auto-correlation with the method of Newey and West (1987). The lags are selected according to the Akaike information criterion (AIC). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), the United States, (US), Denmark (DK), the Czech Republic (CZ), Poland (PL) and Israel (IL).

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	US	DK	CZ	PL	IL
Panel A: Quarterly Regressions pooled averages																
b1	0.73***	0.61***	0.71***	0.74***	0.71***	0.72***	0.71***	0.73***	0.84***	0.63***	0.56***	0.45***	0.70***	0.64***	0.50***	0.55***
	(13.26)	(9.7)	(8.08)	(9.89)	(10.92)	(12.87)	(10.78)	(7.98)	(12.53)	(7.53)	(5.41)	(6.32)	(6.98)	(9.62)	(8.83)	(8.62)
b2	0.05*	0.02**	0.01	0.02	0.02	−0.01	0.00	0.02**	0.00	0.03***	0.01	0.10***	0.00	0.01	0.03	0.01
	(1.94)	(2.35)	(0.98)	(1.35)	(1.08)	(−0.57)	(−0.15)	(2.00)	(0.9)	(2.72)	(0.24)	(3.44)	(−0.08)	(0.28)	(1.19)	(0.47)
b3	0.05	0.01	0.01	0.01	0.04	−0.01	0.02	0.02	0.01	−0.01	−0.01	0.13***	0.01	−0.01	0.00	0.00
	(1.38)	(1.08)	(1.37)	(0.90)	(1.62)	(−0.66)	(0.48)	(1.47)	(0.61)	(−1.53)	(−0.60)	(3.22)	(1.00)	(−0.72)	(0.07)	(0.14)
SUM	0.83***	0.65***	0.73***	0.77***	0.77***	0.71***	0.72***	0.78***	0.85***	0.65***	0.56***	0.68***	0.71***	0.64***	0.53***	0.57***
	(9.21)	(11.99)	(9.03)	(10.27)	(14.31)	(13.06)	(9.42)	(7.57)	(13.43)	(7.85)	(4.35)	(10.07)	(8.68)	(10.14)	(6.87)	(6.89)
Panel B: Fama MacBeth Regressions																
b1	0.72***	0.62***	0.70***	0.74***	0.69***	0.72***	0.69***	0.69***	0.84***	0.62***	0.53***	0.33	0.69***	0.64***	0.57***	0.51***
	(24.59)	(9.11)	(9.81)	(31.63)	(16.44)	(15.67)	(28.85)	(8.27)	(25.98)	(8.29)	(3.36)	(1.03)	(26.79)	(18.98)	(6.23)	(12.28)
b2	0.05**	0.02*	0.01	0.01	0.02	−0.01	−0.01	0.02***	0.00**	0.03***	0.02	0.11**	0.00	0.00	0.02	0.01
	(2.21)	(1.86)	(1.45)	(1.10)	(1.12)	(−0.80)	(−0.81)	(2.62)	(2.32)	(4.46)	(0.62)	(2.09)	(0.1)	(0.03)	(0.78)	(0.73)
b3	0.05**	0.01*	0.01	0.01*	0.05*	−0.01	0.03	0.02**	0.01	−0.01*	0.00	0.15*	0.01	−0.02	−0.01	0.00
	(2.01)	(1.72)	(1.41)	(1.95)	(1.94)	(−0.98)	(0.99)	(2.02)	(0.69)	(−1.73)	(−0.15)	(1.92)	(0.77)	(−1.23)	(−0.14)	(−0.29)
SUM	0.83***	0.65***	0.72***	0.77***	0.76***	0.70***	0.70***	0.73***	0.85***	0.64***	0.55***	0.60***	0.70***	0.62***	0.58***	0.52***
	(16.55)	(8.33)	(10.75)	(22.04)	(25.4)	(12.16)	(19.18)	(9.78)	(34.7)	(8.27)	(2.74)	(4.27)	(37.42)	(9.83)	(6.49)	(9.67)

and average now at 0.656 (pooled panel) and 0.658 (Fama-MacBeth). This suggests that long-term bonds (that have now higher weights) are significantly more exposed to market wide liquidity changes. The weighting of the time periods that differs between the two approaches (as explained above) does not seem to influence the results much (small differences in coefficients across the two versions).[17]

3.2. Commonality over time

Kamara et al. (2008) and Karolyi et al. (2012) document that commonality in liquidity (in equity markets) varies over time. Fig. 2 plots the average correlation of the liquidity of a single bond with the market (all the other bonds) on a quarterly basis for Germany, Austria, Italy and Portugal. The plots show that the degree of commonality varies substantially over time in sovereign bond markets as well.[18] In the Italian market for example the quarterly correlation coefficients average at 0.44 but can be as low as 0.06 in Q1 2007 or as high as 0.92 in Q4 2014.

As in Karolyi et al. (2012) we attempt to link the time variation in commonality in liquidity to potential drivers (common determinants of the liquidity of all or a group of bonds). One hypothesis is that increased institutional ownership gives rise to correlated trading across stocks which can create common buying or selling pressure and thus higher levels of common variation in liquidity. Consistent with this, Kamara et al. (2008) show that institutional ownership is high for stocks that exhibit high commonality and that changes in institutional ownership over time can explain the increase in commonality in liquidity in the US between 1963–2005. Similarly, Koch et al. (2016) relate the commonality in liquidity among US stocks to correlated trading behavior of mutual funds.

While these papers relate the existence of commonality in liquidity to demand side factors Brunnermeier and Pedersen (2008) have developed a theoretical model that shows how commonality can arise from supply determinants of liquidity. In the model liquidity providers face funding constraints. Investors get financing by posting margins. This setup can lead to a situation that Brunnermeier and Pedersen (2008) call a liquidity spiral, where initial losses cause funding problems for speculators leading to reduced liquidity provision in all securities.[19] In line with Brunnermeier and Pedersen (2008) the paper of Comerton-Forde et al. (2010) finds that the liquidity provision of banks is related to their financial performance. Consistent with this Nyborg and Östberg (2014) show empirically that tight funding conditions lead to liquidity pull back possibly contributing to common movements in liquidity. In addition to that Hameed et al. (2010) find that commonality increases in times of high volatility and Coughenour and Saad (2004) provide evidence that common market makers can increase commonality in liquidity.

[17] An exception is the US. The reason for this is that the data provider changed (as discussed in the data section). Commonality is much higher when the GovPX consensus quotes are used as opposed to the ICAP best prices.

[18] Plots look similar in the other markets this paper covers.

[19] Similar effects arise in the theoretical models of Gârleanu and Pedersen (2007), Gromb and Vayanos (2002), Kyle and Xiong (2001) and Vayanos (2004). See Karolyi et al. (2012) for a more extensive summary.

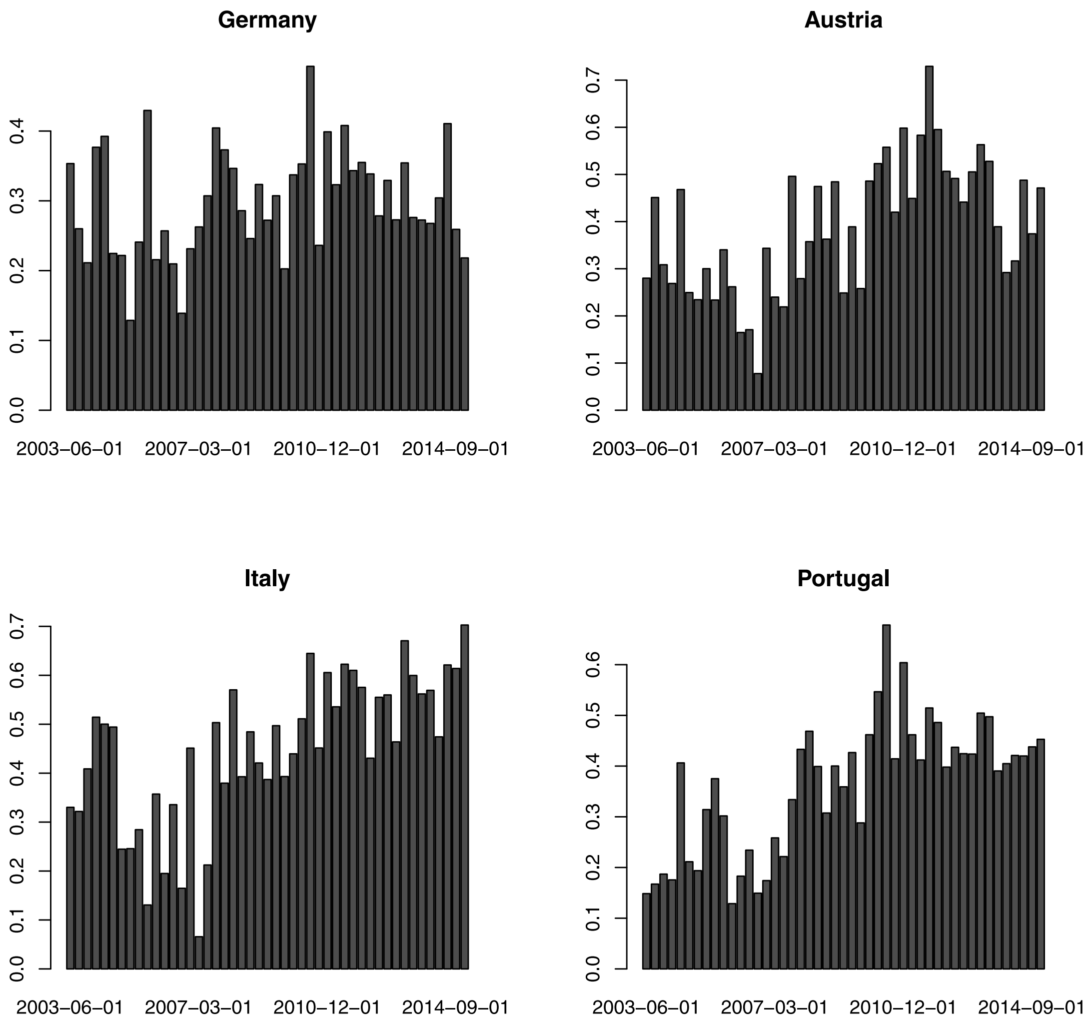

Fig. 2. Commonality in liquidity over time. This figure plots the average correlation of the first differences in liquidity (relative quoted bid–ask spread calculated from intraday quote data) of a single bond with the market (all the other bonds) on a quarterly basis for Germany (top left), Austria (top right), Italy (bottom left) and Portugal (bottom right).

In line with Karolyi et al. (2012) we collect variables that proxy for these demand and supply side explanations of liquidity and relate them to commonality in liquidity. In this context commonality in liquidity is measured by the average correlation $\rho_{BM,t}$ between the change in liquidity of bond B with the market M (average liquidity of all bonds except bond B) for all securities in a given month in a country. Besides market conditions and variables proxying for differences in the economic structure (changes in market liquidity, interest rates, stock market returns, volatility, and sovereign bond returns) we consider the local bank returns, the short rate and the number of market makers as supply side factors. Local bank returns measure the financial health of funding agents (Karolyi et al., 2012).[20] To proxy for demand side factors we look at the ZEW sentiment index, exchange rate changes and % of buy orders as an indicator for buying pressure.[21]

Having collected these variables, we relate the monthly correlation in liquidity changes to these factors. As proposed by Karolyi et al. (2012) we estimate the coefficients in a seemingly unrelated regression system with an equation for each country and restrict the coefficients to be equal across the different equations (countries). This has three advantages (1) it allows us to exploit the panel structure of the data even though we have a small number of countries in the cross-section, (2) the joint estimation is more efficient and (3) the results are more tractable because of the coefficient restrictions (one system coefficient as opposed to single coefficients for each market). A drawback is however that we have to exclude countries with missing observations (the model requires a balanced

[20] Note that the local bank returns are based on the local FTSE bank index and are not exactly matched to the market makers on the MTS platform.

[21] The definition and calculation as well as the data sources of these variables can be found in Table A.1 Panel A in Appendix.

Table 5
Commonality in liquidity over time. This table reports the results of time series regressions that relate the degree of commonality measured as the average correlation between the change in liquidity of bond B and the change in market liquidity (all other bonds) in 10 countries (Austria AT, Belgium BE, Germany DE, Spain ES, Finland FI, France FR, Ireland IE, Italy IT, Netherlands NL and Portugal PT) to a set of country-specific time-series variables as follows:
$\bar{\rho}^{BM}_{M,t} = \alpha + \sum_j \beta_j X^j_{M,t} + \sum_j \gamma_j Z^j_{M,t} + \delta t + \epsilon_{M,t}$,
where $X^j_{M,t}$ proxies for J supply side determinants of liquidity as well as market conditions (liquidity, volatility, returns, time trend, stock market returns, interest rates (10 year government bond rate and the crisis) and $Z^j_{M,t}$ denotes K demand side determinants of liquidity. The considered demand side factors include the ZEW economic sentiment index (ZEW), absolute changes in the exchange rate (FXR) as well as a measure for buying pressure (% of buyer initiated trades, BYP). Supply side factors in the model are local bank returns (LBR), the short rate (SRT) and the number of market makers (NMM). Detailed variable definitions can be found in Table A.1 Panel A. The equations are estimated jointly for the 10 countries using the seemingly unrelated regression technique (SUR) with the restriction that the estimated coefficients are the same for all countries. ***, **, * denote statistical significance at the 1%, 5% and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	−4.103	−6.318	−1.294	−6.361	−6.026	−1.681
	(−0.25)	(−0.39)	(−0.08)	(−0.39)	(−0.37)	(−0.1)
Volatility	−24.399*	−23.298	−13.054	−21.666	−30.965**	−22.832
	(−1.69)	(−1.62)	(−0.93)	(−1.5)	(−2.14)	(−1.63)
Return	−12.401	−10.159	−2.031	−13.889	−10.121	−7.158
	(−1.42)	(−1.16)	(−0.23)	(−1.59)	(−1.16)	(−0.83)
Interest Rates	0.021***	0.02***	0.016***	0.02***	0.022***	0.02***
	(4.82)	(4.47)	(3.73)	(4.48)	(5.02)	(4.48)
Stock Market		−6.943***	−7.473***		−8.269***	−7.799***
		(−2.99)	(−3.25)		(−3.67)	(−3.41)
Time Trend	0.001***	0.001***	0.002***	0.001***	0.001***	0.002***
	(3.38)	(4.20)	(5.29)	(4.13)	(2.62)	(5.07)
Crisis	0.077**	0.065**	0.074***	0.067**	0.068**	0.077***
	(2.56)	(2.25)	(2.76)	(2.3	(2.39	(2.84
ZEW	0.000					
	(1.33)					
FXR		1.790				
		(0.24)				
BYP			0.099**			
			(2.24)			
LBR				−0.007**		
				(−2.12)		
SRT					−0.018**	
					(−2.33)	
NMM						0.003***
						(4.13)
McEltroy R^2	0.030	0.045	0.063	0.032	0.056	0.071
N (system)	1410	1410	1200	1410	1410	1200

panel).[22] We estimate:

$$\bar{\rho}^{BM}_{M,t} = \alpha + \sum_j \beta_j X^j_{M,t} + \sum_j \gamma_j Z^j_{M,t} + \delta t + \epsilon_{M,t}, \tag{3}$$

where $X^j_{M,t}$ are j proxies for market conditions and supply side variables corresponding to market M and month t. The Z variables proxy for demand side explanations. Table 5 contains the results. Consistent with supply side explanations of liquidity commonality, the results show that commonality increases when interest rates are high (funding constraints) and during the crisis. According to specification (1) in Table 5 a one standard deviation increase in the interests rates leads to a 3.4% increase in the average correlations. Consistent with this commonality is more pronounced in the crisis period (the correlation coefficient increases by 7.7% in specification (1) of Table 5). Additionally, one can observe that commonality in liquidity is increasing over time.

The results further indicate that commonality in liquidity is negatively correlated with local bank returns. This is consistent with the view that if market makers' (making markets in many securities) capital constraints (as a consequence of experiencing negative returns) tighten, liquidity decreases for many bonds, at the same time leading to an increased correlation across bonds. A one standard deviation decrease in local bank returns leads to an increase of the average correlation coefficient of 1.10%. A high number of market makers per bond implies that several bonds have the same market makers leading to more correlation in liquidity of bonds that share (a) market maker(s). According to the regression estimates an increase in the number of market makers (by one) leads to a moderate increase in correlations of 0.30%.

[22] The system is estimated using data from Austria (AT), Belgium (BE), Germany (DE), Finland (FI), France (FR), Italy (IT), Spain (ES), Portugal (PT), Ireland (IE), Netherlands (NL) and the (US). This means we do not consider Poland (PL), the Czech Republic (CZ), Denmark (DK), Israel (IL) and Greece (GR).

Apart from these potential supply-driven determinants of common liquidity movements we are interested in the demand-side explanations. Results show that commonality in liquidity in sovereign bond markets is not influenced by changes in the exchange rates or the economic sentiment (unlike in equity markets as shown by Karolyi et al. (2012) and discussed in the introduction). However, a one standard deviation increase in buy orders leads to a 0.96% increase in commonality in Liquidity which is statistically significant.

Overall, the results suggest that both demand and supply side determinants of liquidity drive common movements in liquidity in sovereign bond markets. However, opposed to the findings in equity markets (Karolyi et al., 2012) supply side factors play a much more important role in bond markets. An explanation for this might be that the bond market depends more on a few dealers to supply liquidity as opposed to a broad number of market participants that interact with each other in a limit order book market.

3.3. Global and cross-market commonality

So far, we have analyzed common movements in liquidity within national sovereign bond markets. Next we want to test whether there are also co-movements in liquidity across markets. Brockman et al. (2009) have found global commonality across international equity markets. Moreover, commonality in liquidity has been shown by to exist in foreign exchange markets (Karnaukh et al., 2015; Mancini et al., 2013; Sensoy et al., 2021). We follow the approach of Brockman et al. (2009) and test for the existence of a global liquidity factor by relating changes in the liquidity in one market to global changes in liquidity (changes in liquidity in all other markets) as follows:

$$\begin{aligned}\Delta LIQUIDITY_{M,t} &= \alpha + \beta_1 \Delta LIQUIDITY_{G,t} + \beta_2 \Delta LIQUIDITY_{G,t-1} \\ &+ \beta_3 \Delta LIQUIDITY_{G,t+1} + \delta_1 RETURN_{M,t} + \delta_2 RETURN_{M,t-1} \\ &+ \delta_3 RETURN_{M,t+1} + \delta_4 \Delta VOLATILITY_{M,t} + \epsilon_{B,t},\end{aligned} \quad (4)$$

where we calculate global liquidity $\Delta LIQUIDITY_{G,t}$ as the equally weighted average of the liquidity of all the markets in the sample except the market whose liquidity is used as the dependent variable. Unlike the evidence documented in Brockman et al. (2009), for equity markets our results do not show much evidence for global commonality in liquidity. The results of estimating Eq. (4) are collected in Table 6. The results reveal that the sensitivity of the liquidity of sovereign bond markets to global sovereign bond liquidity is economically small. The average sum of the β coefficients is 0.017 (median 0.037), becomes occasionally negative and ranges between −0.72 (Greece) and 0.23 (Ireland). In addition to that the variation in local market level liquidity that can be explained by global level liquidity changes is only 1.1% which corresponds to only 14% of the overall variance explained by the model.

Even though economically small, the relations appear to be statistically significant for some countries. A closer look reveals that all these countries are members of the European monetary union (EMU). The median sum of the β coefficients for these countries is 0.066 and the average additional R^2 due to global liquidity is 0.1017. In contrast, sovereign bond markets in Israel, the US, Denmark the Czech Republic, and Poland show no exposure to global liquidity (both the median sum β coefficient and the additional R^2 are 0). Interestingly, two countries that were highly affected by the sovereign debt crisis Portugal and Greece show very little or even negative exposure to the global liquidity factor.

Overall, these results do not support the existence of an economically meaningful global liquidity factor. The significant exposures of some EMU countries seem to be attributable to the high weight of EMU countries in the sample and thus in the calculation of the global liquidity factor rather than the presence of a global liquidity factor. However, these results seem to be suggestive of a common liquidity factor in the euro area. This points towards the importance of individual cross-market relationships which we will explore in more detail.

We start by analyzing the correlations of the liquidity levels between the markets in our sample over time. Fig. 3 plots the correlations between the German and US market and the other 15 markets in the sample for each year. The plot already reveals some interesting patterns. In the case of Germany, we can see that correlations are low before 2007. They tend to be positive but become negative occasionally. During the financial crisis the correlations increase substantially between EMU countries but decrease notably vis-a-vis outside markets in particular the US. During the European sovereign debt crisis correlations remain on a high level but slowly revert to pre-crisis levels.

The picture for the US treasury market is very different. Liquidity in the US market is barely related to other markets in the pre-crisis period. During the financial crisis liquidity in the US treasury market diverges from the rest of the world especially European countries. Co-movements rise substantially in the 2011–2012 period but revert to low levels in 2013 while we see normalization again in 2014. These developments can also be seen in Fig. 4 which plots liquidity in the German, Dutch, Italian, Spanish and US markets over the entire sample period on a weekly frequency.

In a next step we further want to understand what factors drive these co-movements. To study this, we calculate the correlations between the liquidity for all our country pairs. This means towards the end of the time period we observe 120 country pairs (fewer in earlier periods because we have no data for some countries in earlier periods). Given that market conditions such as returns and the volatility impact commonality in liquidity within markets their correlation across markets could also explain cross-market liquidity commonality. We thus consider the monthly correlation between the volatility and the market returns of a country pair (ρ^{Return} and $\rho^{Volatility}$) as additional variables.

Furthermore, we consider global or pair-specific supply and demand side factors. While we have seen before that local bank returns can lead to joint development of liquidity of many bonds, we now check whether returns of globally operating banks (who

Table 6
Global commonality. This table contains the results of estimating a time series regression for each market that relates the liquidity of this market $\Delta LIQUIDITY_M$ to the liquidity of the other markets $\Delta LIQUIDITY_G$ while controlling for global returns $RETURN_G$ and changes in volatility $VOLATILITY_M$ as follows:
$\Delta LIQUIDITY_{M,t} = \alpha + \beta_1 \Delta LIQUIDITY_{G,t} + \beta_2 \Delta LIQUIDITY_{G,t-1} + \beta_3 \Delta LIQUIDITY_{G,t+1}$
$+\delta_1 RETURN_{G,t} + \delta_2 RETURN_{G,t-1} + \delta_3 RETURN_{G,t+1} + \gamma_4 \Delta VOLATILITY_{M,t} + \epsilon_{M,t}$.
The first row reports the average β_1 coefficients for each market (t-statistics in parenthesis). The second and third row report the β_2 and β_3 coefficients. The t-statistics are based on standard errors calculated with the method of Newey and West (1987) with $\sqrt[4]{N}$ lags. The fourth row shows the sum of the coefficients associated to the contemporaneous, lead and lag changes in global liquidity $SUM = \beta_1 + \beta_2 + \beta_3$. The p-value below is obtained from an F-test that tests whether all three coefficients are jointly zero. The last three rows contain the adjusted R^2 for all variables, the adjusted R^2 that is generated from the addition of the market liquidity variables and the number of observations (N). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), the United States, (US), Denmark (DK), the Czech Republic (CZ), Poland (PL) and Israel (IL).

	AT	BE	DE	ES	FI	FR	GR	IE
Concurrent	0.085***	0.057***	0.018***	0.095**	0.035***	0.023***	0.388	0.173
	(4.75)	(3.64)	(3.49)	(2.08)	(3.65)	(2.86)	(0.46)	(1.16)
Lag	0.048***	0.023**	0.010***	0.033	0.026***	0.005	−0.409	0.093
	(3.24)	(2.05)	(3.99)	(0.83)	(3.25)	(0.52)	(−0.41)	(0.79)
Lead	0.035***	0.026**	0.002	0.048*	0.005	0.014	−0.699	−0.036
	(3.35)	(2.31)	(0.72)	(1.81)	(0.58)	(1.64)	(−0.85)	(−0.27)
SUM	0.168***	0.106***	0.03***	0.176***	0.066***	0.043***	−0.72	0.23*
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.08
R^2	0.218	0.145	0.062	0.013	0.119	0.025	−0.001	0.140
add R^2	0.024	0.021	0.036	0.010	0.018	0.004	0.001	0.003
N	2979	2979	2979	2979	2979	2979	2458	2979
	IT	**NL**	**PT**	**US**	**DK**	**CZ**	**PL**	**IL**
Concurrent	0.060***	0.024***	0.127	0.000	0.007	−0.006	0.029	−0.001
	(3.27)	(3.82)	(1.10)	(0.48)	(1.51)	(−0.55)	(1.44)	(−0.44)
Lag	0.026***	0.014***	0.017	0.000	−0.004	−0.001	−0.006	−0.001
	(2.78)	(2.77)	(0.15)	(0.58)	(−1.05)	(−0.08)	(−0.27)	(−1.04)
Lead	0.020***	0.008***	−0.118	0.000	0.004	−0.014*	−0.005	−0.002
	(2.68)	(2.59)	(−1.11)	(−0.55)	(1.29)	(−1.75)	(−0.21)	(−0.64)
SUM	0.105***	0.046***	0.026	0.000	0.006	−0.021	0.019	−0.004
p-value	0.00	0.00	0.82	0.83	0.42	0.38	0.86	0.56
R^2	0.096	0.131	0.254	0.002	0.001	0.049	0.025	−0.004
add R^2	0.034	0.026	0.005	0.000	0.002	−0.001	−0.001	−0.002
N	2979	2979	2979	2760	2813	867	2237	1044

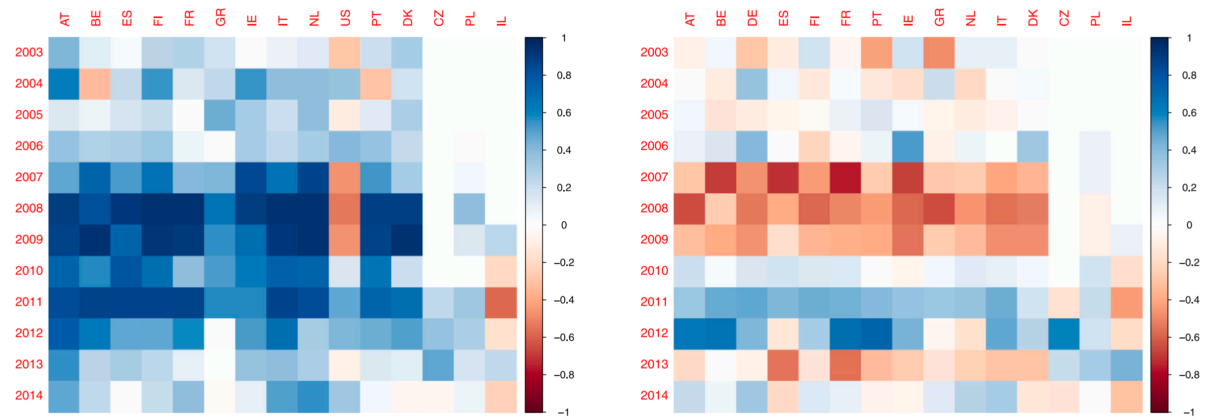

Fig. 3. Cross-market correlations in liquidity Germany and USA. The graph on the right (left) displays the annual correlation between the market liquidity in the US (Germany) and the other 15 countries over the sample period between 2003 and 2014. Each plot shows the country on the x axis and the year on the y axis. A correlation of −1 is plotted dark red and a correlation of +1 dark blue. Values of the correlation coefficient between 0 and 1 are displayed in different shades of blue. Values of the correlation coefficient between −1 and 0 are displayed in different shades of red. The lighter the color the lower the correlation. A correlation of 0 is plotted as white. Similarly, missing values for CZ (until 2009), PL (until 2005) and IL (until 2008) are plotted white as well. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

act as liquidity providers in many markets) are related to increased cross-market liquidity commonality. To proxy for correlated demand, we add absolute exchange rate returns into the model. For each country pair we use the exchange rate between the currencies used there.

In addition to these factors that also play a role within markets we also consider two drivers that are interesting in the context of the analysis of cross-market liquidity (a) common monetary policy and (b) yield spreads. Brockman et al. (2009) and Sensoy

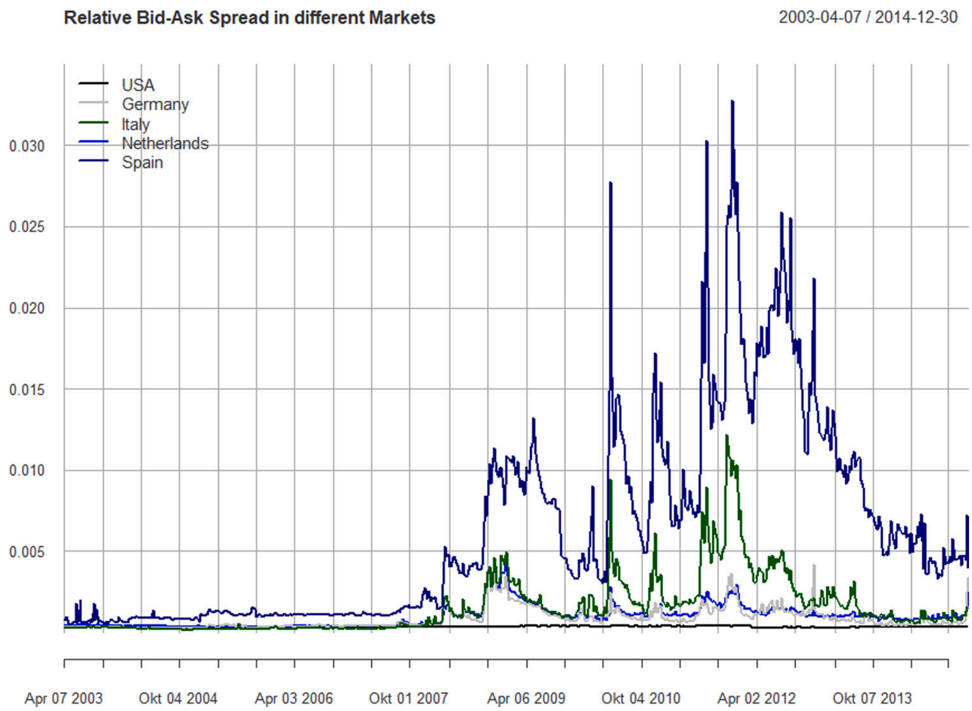

Fig. 4. Development of liquidity in different markets. This graph displays the relative quoted bid–ask spread for the sample bonds between April 2003 and December 2014 on a weekly frequency. The black line shows the bid–ask spread in the US market and is based on daily snapshots from Treasury CRSP. The gray-, dark green-, blue- and navy-colored lines represent Germany, Italy, the Netherlands and Spain and display the bid–ask spread calculated from high-frequency quote data from MTS. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

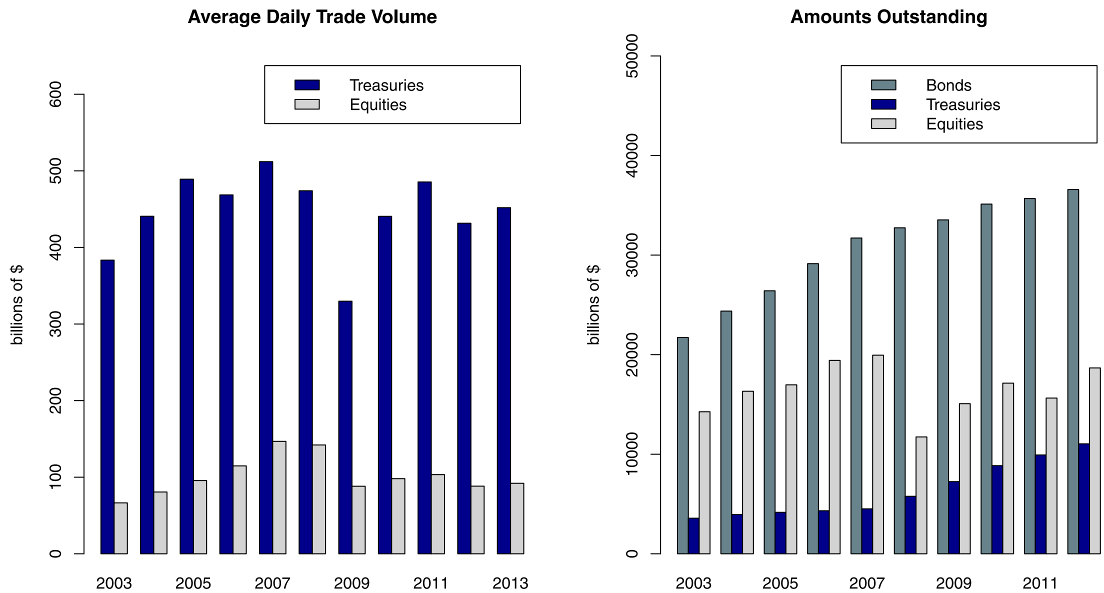

Fig. 5. Trading volume and amounts outstanding. The graph on the left-hand side shows the average daily trading volume in the US treasury (blue bars) and equity market (New York Stock Exchange (NYSE) - gray bar) between 2003 and 2013. The graph on the right-hand side displays the amounts outstanding for US corporate bonds (turquoise bar) and treasuries (blue bar) as well as the market capitalization of NYSE stocks (gray bar). The data source is the Securities Industry and Financial Markets Association (SIFMA). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(2016) relate monetary policy to commonality in liquidity. We investigate the role of a common monetary policy by analyzing the differences between the liquidity correlation in euro and non-euro countries (using an EMU dummy). In addition to that we test

Table 7
Understanding cross-market liquidity relations. This table reports the results of panel regressions that relate the degree of commonality measured as the correlation ρ between the liquidity of two countries in month t for 120 country pairs p ($\frac{(16-1)\times 16}{2}$) to a set of potential explanatory variables as follows:
$\rho_{p,t} = \alpha_p + \sum_j \beta_j X^j_{p,t} + \delta t + \epsilon_{p,t}$.
where $X^j_{p,t}$ proxies for J explanatory variables which include: the correlation between returns in the two markets ρ^{Return}, the correlation between the volatility in the two markets ρ^{SD}, a crisis dummy, a dummy indicating membership in the European Monetary Union (EMU), a dummy for pairs of EMU Core countries (CORE), a dummy for pairs of EMU periphery counties (PERI), the absolute yield spread, the gold price, absolute changes in the FX rate between two countries as well as prime broker returns. A more extensive definition of the variables can be found in Table A.1 Panel B. The equations are estimated as pooled regressions (specification 1, 2 and 3) or as panel models with pair fixed effects. Standard errors are clustered around time. ***, **, * denote statistical significance at the 1%, 5% and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ρ^{Return}	0.244***	0.243***	0.240***	0.218***	0.219***	0.22***	0.22***
	(10.89)	(10.86)	(10.62)	(9.44)	(9.35)	(9.46)	(9.50)
ρ^{SD}	0.04*	0.048**	0.034	0.003	0.01	0.014	0.013
	(1.95)	(2.35)	(1.60)	(0.15)	(0.48)	(0.63)	(0.6)
Time trend	−0.004	−0.007**	−0.004	−0.01**	−0.01*	−0.011**	−0.011**
	(−1.46)	(−2.30)	(−1.50)	(−2.15)	(−1.89)	(−2.35)	(−2.48)
Crisis	0.177***	0.088***	0.174***	0.212***	0.219***	0.214***	0.218***
	(5.93)	(3.66)	(5.80)	(4.92)	(4.81)	(4.96)	(5.19)
EMU	0.183***	0.064***	0.181***				
	(10.7)	(2.87)	(10.59)				
EMU × Crisis		0.175***					
		(5.55)					
PERI			−0.011				
			(−0.84)				
CORE			0.040***				
			(3.419)				
$\lvert YieldSpread \rvert$				−0.015***			
				(−4.07)			
Gold					−0.034		
					(−0.47)		
$\lvert \Delta FX \rvert$						0.196	
						(0.52)	
Prime Broker Returns							0.053
							(0.5)
Pair FE	No	No	No	Yes	Yes	Yes	Yes
Cluster	Time	Time	Time	Time	Time	Time	Time
R2	0.174	0.185	0.174	0.07	0.069	0.069	0.069
N	13,765	13,765	13,765	13,765	13,765	13,765	13,765

whether the flight-to-safety phenomenon plays a role in the decoupling of liquidity across market since liquidity may dry up in one market and concentrate in another (Longstaff, 2009). We use absolute yields spreads (of 10-year benchmark bonds of two countries) and the gold price to proxy for flights-to-safety.[23] Finally, we estimate the following panel regression:

$$\rho_{p,t} = \alpha_p + \sum_j \beta_j X^j_{p,t} + \delta t + \epsilon_{p,t} \tag{5}$$

where $\rho_{p,t}$ is the correlation of the liquidity between pair p (e.g. Germany and Italy) in month t, α_p are pair fixed effects and X^j is a set of potential explanatory factors as described above. The coefficient estimates are collected in Table 7.

Not surprisingly the results indicate that country pairs that exhibit co-movement in market conditions (returns and volatility) also exhibit higher commonality in liquidity. Based on specification (1) a one standard deviation increase in the return correlations (volatility correlations) leads to an increase in liquidity correlations of 0.081 (0.075). Moreover, the results show that cross-market correlations are 0.183 higher among members of the European monetary union (EMU) compared to mixed or non-EMU pairs. This suggests that a common monetary policy can induce liquidity co-movements.

The results also show that the crisis led to an increase in liquidity correlations. Specification (1) suggests that the crisis led to an increase in correlations of 0.177. Specification (2) shows that the increase has been moderate for mixed or non-EMU country pairs (increase of 0.088) but huge for EMU country pairs (an additional increase of 0.175). In specification (3) we distinguish between correlations among EMU periphery and EMU core country pairs. The results show that country pairs consisting of two core countries exhibit even higher correlations. In specification (4) we explore what happens to correlations in liquidity in flight-to-safety episodes. The results indicate that a high absolute yield spreads between two countries indicates a decoupling of liquidity in these two countries. A one standard deviation increase of the absolute yield spreads reduces the correlations by 0.01. We also use the gold price as an indicator for flight-to-safety episodes. Consistent with intuition a high gold price is associated with lower correlations among the country pairs, but the relation is not statistically significant.

[23] The definition and calculation as well as the data sources of these variables can be found in Table A.1 Panel B in Appendix.

Table 8

Robustness commonality in liquidity Japan and UK. This table contains the results of estimating the regressions to detect local commonality in line with the description in Table 3. The tables shows the results for Japan (JP) and the United Kingdom (UK) based on Bloomberg data. The first four rows in the table below report the average β_1 coefficient, the associated t-statistic (in parenthesis), the % of positive coefficients as well as the % of positive significant coefficients. The t-test is based on the cross-sectional variation across all the estimated regression coefficients within a country. The percentage of positive and significant coefficients is based on the t-statistic associated with the regression coefficient in the single time series regression which has been estimated using the method of Newey and West (1987) - assessment of significance at the 10% level. Rows 5–8 and 9–12 contain the same statistics for the β_2 and the β_3 coefficients (lead and lag). Row 13 shows the average sum of the coefficients $SUM = \beta_1 + \beta_2 + \beta_3$. Row 15 shows the median of this sum (associated p-values are based on a sign test). The last two rows contain the adjusted R^2 for the entire regressions as well as the part that comes from the addition of the market liquidity variables (contemporaneous, lead and lag). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Japan (JP) and the United Kingdom (UK).

	UK	JP
β_1	0.57***	0.59***
	(10.28)	(12.80)
%positive	84.7%	77.9%
%positive*	60.2%	29.2%
β_2	−0.03	0.01
	(−1.29)	(1.03)
%positive	42.9%	50.5%
%positive*	8.5%	5.9%
β_3	−0.01	0.03***
	(−0.28)	(2.69)
%positive	49.1%	53.1%
%positive*	13.9%	6.6%
SUM	0.54***	0.64***
	(8.62)	(11.05)
Median	0.11***	0.10***
p-value	0.00	0.00
R^2 add	0.051	0.043
R^2 mean	0.056	0.047
N	352	1632

Absolute changes in the exchange rates between two countries cannot explain changes in correlations. Interestingly, the global prime broker returns are also not able to explain significant variation in liquidity correlations. Together with the results obtained in Section 3.2 this suggests that liquidity provision is more driven by local factors (local bank returns) as opposed to global factors (prime broker returns). This observation is also consistent with the finding that there seems to be no global liquidity factor, but that there are strong cross-market liquidity linkages.

4. Robustness

4.1. Inclusion of Japanese and UK sovereign bond markets

The UK and the Japanese sovereign bond markets are the second and third largest sovereign bond markets in the world. However, they have not been covered in our analysis so far. The reason for this is entirely data related, because the two markets are not represented well in the MTS and the Treasury CRSP data set.[24] In order to show that our baseline results about local commonality also hold in these important markets we gathered additional data on sovereign bonds from the UK and Japan from Bloomberg.

We follow the same approach and calculate the same metrics as in Section 3.1. Table 8 contains the result for the UK and Japan. Overall, we considered 1632 Japanese bonds and 352 UK bonds. The results are in line with the ones for the other countries in Table 3. The β coefficients resembling the relation between (local) market liquidity and a bonds individual liquidity are positive and significantly different from zero. The β_1 coefficient for the UK is 0.57 and the one for Japan is 0.59. The numbers are very similar, in terms of R^2 as well as concerning the number of significant coefficients β in the single regressions. Overall, it is re-assuring that our results generalize to different countries and remain valid when the liquidity data is sourced from a different database (here Bloomberg).

[24] The MTS data set does not contain any data about Japanese government bonds. Moreover, the MTS data for the UK is scarce. The data set contains only a small fraction of the bonds outstanding and only for a very short time period.

Table 9

Robustness volatility measure. This table contains the results of estimating the regressions to detect local commonality in line with the description in Table 3 except for the volatility measure. For the regression and analysis in this table the Garman and Klass volatility estimator is used). The tables shows the results for Belgium (BE), Germany (DE), Spain (ES), France (FR) and (IT). The first four rows in the table below report the average β_1 coefficient, the associated t-statistic (in parenthesis), the % of positive coefficients as well as the % positive significant coefficients. The t-test is based on the cross-sectional variation across all the estimated regression coefficients within a country. The percentage of positive and significant coefficients is based on the t-statistic associated with the regression coefficient in the single time series regression which has been estimated using the method of Newey and West (1987) - assessment of significance at the 10% level. Rows 5–8 and 9–12 contain the same statistics for the β_2 and the β_3 coefficients (lead and lag). Row 13 shows the average sum of the coefficients $SUM = \beta_1 + \beta_2 + \beta_3$. Row 15 shows the median of this sum (associated p-values are based on a sign test). The last two rows contain the adjusted R^2 for the entire regressions as well as the part that comes from the addition of the market liquidity variables (contemporaneous, lead and lag). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Belgium (BE), Germany (DE), Spain (ES), France (FR) and Italy (IT).

	BE	DE	ES	FR	IT
β_1	0.38***	0.56***	0.61***	0.47***	0.43***
	(9.90)	(18.02)	(7.18)	(11.6)	(17.03)
%positive	93.6%	95.7%	94.6%	87.6%	98.1%
%positive*	67.8%	79.0%	68.9%	51.1%	76.4%
β_2	0.03***	0.03**	0.05*	−0.01	0.03***
	(4.71)	(2.35)	(1.83)	(1.41)	(3.86)
%positive	68.2%	58.0%	58.0%	56.3%	61.4%
%positive*	16.5%	12.7%	9.7%	10.0%	17.9%
β_3	0.01	0.03**	0.053*	0.00	0.01**
	(1.11)	(2.13)	(1.87)	(−0.16)	(2.08)
%positive	64.0%	59.6%	54.1%	54.4%	56.1%
%positive*	12.3%	10.0%	10.5%	13.1%	8.6%
SUM	0.42***	0.62***	0.71***	0.45***	0.47***
	(10.48)	(17.8)	(5.46)	(12.12)	(16.55)
Median	0.12***	0.46***	0.37***	0.15***	0.24***
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2 add	0.093	0.079	0.108	0.067	0.143
R^2 mean	0.229	0.246	0.249	0.197	0.286
N	236	371	257	458	474

4.2. Alternative volatility measures

In the previous section we used the intraday standard deviation as well as the squared return (close-to-close) to measure daily volatility. The choice of this calculation methods is well founded based on considerations of the data. However, a robustness test with a different volatility measure is merited because (a) as pointed out by Chordia et al. (2000) volatility is the most important control variable in the regressions used to detect and analyze commonality in liquidity, (b) there are many different measures that can potentially be used and (c) the choice of the measure can impact the results of an analysis (Molnár, 2012).

Molnár (2012) advocates the use of a volatility measure that was first suggested by Garman and Klass (1980) which is the best performing volatility measure in the study. Apart from this the measure is used in Sensoy et al. (2021) which also studies commonality in liquidity using high-frequency data. We follow the calculation logic of Molnár (2012).[25] The Garman and Klass (1980) volatility estimator is a range-based measure. It can be calculated based on high, low, open and close prices and is widely used in the literature.

We therefore re-estimate our baseline regressions for selected markets using the Garman and Klass (1980) estimator instead of the previously applied volatility estimator. Table 9 contains the results of these regressions. By comparing the estimates in Tables 3 and 9 we can see that they are quantitatively and qualitatively similar. This suggests that our results are robust to the choice of the volatility measure.

4.3. Volume-weighting and global commonality

In Section 3.3 we have use a equally weighted average to calculate global liquidity in line with the previous literature (Brockman et al., 2009). In this section we want to investigate whether our results are robust to the use of a volume-weighted index that also includes Japan and the UK. We calculate annual weights based on the BIS public debt statistics. Table 10 shows the results.

The results show that using a volume-weighted average does not alter our conclusions. The results once again show statistically significant results for most of the EMU countries. The weight of the EMU countries together in the global liquidity aggregate is still substantial. However, there is still very little evidence for global commonality in liquidity for markets outside the EMU. Most

[25] There are many versions of the estimator. We use equation (15) in Molnár (2012) to calculate the measure.

Table 10

Volume-weighted Global Commonality. This table contains the results of estimating a time series regression for each market that relates the liquidity of this market $\Delta LIQUIDITY_M$ to the volume-weighted liquidity of the other markets $\Delta VWLIQ_G$ while controlling for volume-weighted global returns $VWRET_G$ and changes in volatility $VOLATILITY_M$ as follows:

$\Delta LIQUIDITY_{M,t} = \alpha + \beta_1 \Delta VWLIQ_{G,t} + \beta_2 \Delta VWLIQ_{G,t-1} + \beta_3 \Delta VWLIQ_{G,t+1}$
$+\delta_1 VWRET_{G,t} + \delta_2 VWRET_{G,t-1} + \delta_3 VWRET_{G,t+1} + \gamma_4 \Delta VOLATILITY_{M,t} + \epsilon_{M,t}.$

The first row reports the average β_1 coefficients for each market (t-statistics in parenthesis). The second and third row report the β_2 and β_3 coefficients. The t-statistics are based on standard errors calculated with the method of Newey and West (1987) with $^4\sqrt{N}$ lags. The fourth shows the sum of the coefficients associated to the contemporaneous, lead and lag changes in global liquidity $SUM = \beta_1 + \beta_2 + \beta_3$. The p-value below is obtained from an F-test that tests whether all three coefficients are jointly zero. The last three rows contain the adjusted R^2 for all variables, the adjusted R^2 that is generated from the addition of the market liquidity variables and the number of observations (N). ***, **, * denote statistical significance at the 1%, 5% and 10% level. The table includes the following countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT), the United States, (US), Denmark (DK), the Czech Republic (CZ), Poland (PL), Israel (IL), Japan (JP) and the United Kingdom (UK).

	AT	BE	DE	ES	FI	FR	GR	IE	IT
Concurrent	0.879***	0.501***	0.165***	1.18***	0.277***	0.187***	0.559	1.624	0.439**
	(3.75)	(3.4)	(3.76)	(2.85)	(4.12)	(2.78)	(0.2)	(1.62)	(2.28)
Lag	0.435*	0.043	0.04	0.329	0.1**	−0.004	−0.300	0.648	−0.010
	(1.83)	(0.6)	(1.54)	(1.3)	(2.29)	(−0.05)	(−0.15)	(0.60)	(−0.11)
Lead	0.174	0.126*	0.046**	0.272	0.112**	0.116*	−1.048	−0.585	0.21*
	(1.54)	(1.67)	(2.19)	(1.51)	(2.17)	(1.71)	(−0.43)	(−0.70)	(1.93)
SUM	1.488	0.669	0.25	1.781	0.489	0.299	−0.789	1.686	0.639
pval	0.00	0.00	0.00	0.00	0.00	0.00	0.837	0.011	0.00
R^2	0.349	0.186	0.032	0.049	0.213	0.026	−0.001	0.126	0.139
add R^2	0.044	0.05	0.021	0.048	0.022	0.01	−0.001	0.014	0.032
N	2979	2979	2979	2979	2979	2979	2458	2979	2979

	NL	PT	US	DK	CZ	PL	IL	JP	UK
Concurrent	0.234***	1.797**	0.000	0.033	0.028	0.233	0.011	−0.002	0.011
	(4.03)	(2.12)	(0.37)	(1.45)	(0.24)	(1.64)	(0.43)	(−0.42)	(0.92)
Lag	0.096***	0.181	0.000	−0.017	0.05	−0.039	0.010	0.004	0.019
	(2.91)	(0.41)	(−0.46)	(−0.78)	(0.99)	(−0.29)	(0.3)	(0.8)	(1.41)
Lead	0.085***	−0.021	−0.001	0.038	−0.151**	0.114	−0.071	0.004	0.004
	(3.19)	(−0.03)	(−1.61)	(1.34)	(−2.2)	(0.72)	(−1.53)	(0.81)	(0.41)
SUM	0.415	1.957	−0.001	0.053	−0.073	0.308	−0.05	0.007	0.033
p-value	0.00	0.00	0.10	0.13	0.66	0.61	0.48	0.54	0.11
R^2	0.124	0.257	0.01	0.002	0.067	0.015	0.014	0.000	0.001
add R^2	0.036	0.015	0.005	0.003	0.005	−0.001	0.005	0.000	0.000
N	2979	2979	2934	2813	867	2237	1044	2942	2861

notably the liquidity of the US market is still not significantly influenced by global liquidity. The sum of the coefficients (lead, lag, concurrent) is even negative. Interestingly, the liquidity of the countries that have been newly added for the robustness check (the UK and Japan) does not significantly co-move with global liquidity.

5. Conclusion

Using the regression approach developed in Chordia et al. (2000) this paper finds the evidence for common liquidity movements in all the studied sovereign bond markets. We find that the extent to which variation in the liquidity of an individual sovereign bond can be explained by a common factor (market liquidity) is substantially higher in sovereign bond markets than in equity markets. This is consistent with the statements in Fleming and Liu (2016) and Fleming and Remolona (1999) that the liquidity in sovereign bond markets depends largely on (common) public information.

Besides documenting the existence of local commonality, we also study drivers of local commonality. While previous studies such as Karolyi et al. (2012) have found evidence consistent with demand-side explanations and question the importance of funding liquidity as a driver of commonality, our results indicate that in the dealer driven sovereign bond markets commonality is mainly driven by proxies related to the supply of liquidity, such as the number of market makers or local bank returns. This suggests that the drivers of commonality in liquidity are influenced by the market design.

Contrary, to the findings in international equity markets (Brockman et al., 2009) and FX Markets (Karnaukh et al., 2015; Mancini et al., 2013; Sensoy et al., 2021) we do not find conclusive evidence for significant impact of a global liquidity factor. Instead, we find negative cross-market correlations of liquidity across several markets and time periods. Liquidity in sovereign bond markets seems to occasionally diminish from one market but at the same time increase in another market. We relate this decoupling of liquidity correlations to flight-to-safety episodes (using yield spreads as a proxy) and diverging monetary policy (here we exploit the fact that countries in the European Monetary Union are subject to the same monetary policy).

Table A.1
Variable descriptions.

Variable	Description	Source
Panel A: Variables from the time-series regression		
Interest rates	Interest rates are 10Y government bond yields of the respective country	Datastream
Stock market	Refers to the log returns of the stock market index of the country in question	Refinitiv
ZEW	The variable ZEW is an indicator of economic sentiment for the Euro area (EMZEWECSR — used for all the countries except the US) or the US (USZEWECSR — used for the US) published by the Centre for European Economic Research. The values of the indicator show the difference between the share of optimistic and pessimistic analysts regarding the predicted economic development in the next six months. This indicator is published monthly.	Datastream
FXR	This variable is the month-to-month change (first difference) of the exchange rate of a country's currency to the USD (for the US it is the exchange rate to the EUR). The exchange rate used is the WM/Reuters closing spot rate which is based on data provided by Reuters at or around 16:00 in London.	Datastream
BYP	% of buy trades in relation to all trades in a particular month averaged over all bonds in a particular country.	MTS
LBR	Monthly local bank returns are calculated from the FTSE country bank indices for each of the countries as continuously compounded returns.	Datastream
SRT	The short rate is approximated by the yields of 1-year government benchmark bonds in the country in question (shortest maturity available for all the countries in the sample).	Datastream
NMM	Number of market makers that post quotes for the bond in the domestic MTS market averaged across all bonds in a country at each month.	MTS
Panel B: Variables for the investigation of cross-market relations		
Gold	Value of the S&P Goldman Sachs Commodity Index — Gold at the end of the month.	Datastream
FX	Absolute monthly FX rate return of the exchange rate (currency pair of the country pair).	Datastream
Prime broker	Equally weighted average return (continuously compounded) of the following globally active financial institutions: Barclays, BNP Paribas, Goldman Sachs, JP Morgan, Credit Suisse, Morgan Stanley, HSBC, Deutsche Bank, Citigroup and UBS (as in Karolyi et al., 2012).	Datastream
Yield spread	Absolute yield spread between the 10-year yields (constant maturity) of a country pair.	Datastream

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Variable descriptions

See Table A.1.

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