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Sovereign debt ratings and stock liquidity around the World[☆]

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ABSTRACT

This paper studies the impact of sovereign debt rating changes on liquidity for stocks from 40 countries for the period 1990–2009. We find that sovereign rating changes significantly affect stock liquidity. The impact is stronger for downgrades than for upgrades, and is nonlinear in event size. The loss of investment grade has a particularly strong negative impact on stock liquidity. We also find that some stock characteristics and country legal and macroeconomic environment are important in explaining the differences in the impact of sovereign credit rating changes on stock liquidity across countries.

1. Introduction

Sovereign credit ratings provide assessments of the probability of default in government debt. When rating a sovereign bond, credit rating agencies state that they consider a large number of economic and political factors and make qualitative and quantitative evaluations of the security. Consequently, a sovereign credit rating change may unveil important new information about a country and impose a significant externality to its private sector, which can affect investors' incentives to hold stocks. As argued by Borensztein et al. (2007) and Gande and Parsley (2005), among others, the cost of sovereign debt constitutes a benchmark for domestic interest rates, e.g., for the cost of corporate borrowing. Hence, developments in sovereign credit markets have broad implications for the overall economy.

The literature on sovereign rating changes and financial markets has mostly focused on the effects of such externality on equity market index returns (Kaminsky and Schmukler, 2002; Brooks et al., 2004; Martell, 2005), individual stock returns (Martell, 2005; Correa et al., 2013), or bond yields (Cantor and Packer, 1996; Larraín et al., 1997; Gande and Parsley, 2005). Prior studies suggest that sovereign downgrades are generally associated with declines and higher volatility of stock market returns. Surprisingly, the impact of sovereign debt rating changes on stock liquidity in global financial markets has not been explored.[1] This paper attempts to fill this gap in the literature. We study the impact of changes in sovereign credit ratings on daily stock liquidity at the firm level for 40 developed and emerging markets from January 1990 to December 2009. To the best of our knowledge, this is the first study to empirically investigate the impact of sovereign

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[1] Odders-White and Ready (2006) study the contemporaneous relation between stock liquidity and credit ratings as well as the predictive power of liquidity on credit ratings in the U.S. market. On the contrary, we investigate the impact of sovereign debt rating changes on stock liquidity.

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debt rating changes on stock liquidity. We also identify key firm-specific and country-level determinants of corporate stock liquidity changes during sovereign credit events.

We posit that sovereign rating changes can affect stock liquidity through at least three channels.

First, the funding constraints of traders or financial intermediaries (e.g., hedge funds, banks, or market-makers) may affect or be affected by market liquidity (Brunnermeier and Pedersen, 2009). Financial intermediaries make the market by absorbing liquidity shocks subject to funding constraints via posted margins on collateral. When a sovereign credit rating is downgraded and the market declines, financial intermediaries will endure losses in collateral values and, if funding constraints bind, margin limits will be hit, thereby forcing agents to liquidate their positions. Moreover, as long as institutional holders are subject to ownership restrictions based on credit ratings (by corporate governance or legal mandate), a sovereign downgrade will either force the institutional holder to liquidate its position, or will at least provide the institutional holder with a strong incentive to do so. One trader hitting his/her limit in one security can lead to falling prices and liquidity in other securities, making other traders hit their respective limits as well. Thus, the so-called “liquidity spirals” or “liquidity black holes” can arise (Morris and Shin, 2004; Brunnermeier and Pedersen, 2009).

A second linkage between sovereign debt rating changes and stock liquidity can occur when investors try to rebalance their portfolios across borders in the event of a rating change, which induces cross-border capital flows (Kim and Wu, 2008; Gande and Parsley, 2010). Since sovereign downgrades lead to limited access to international capital markets in the future (Dittmar and Yuan, 2008), and more so in the presence of a sovereign rating ceiling, which provides an upper limit for ratings of corporate bonds in the country (Cavallo and Valenzuela, 2010), investors may withdraw their capital from the countries when the downgrade announcement is made. On the other hand, sovereign upgrades may induce more capital flows into the country. Hence, the portfolio rebalancing effect can associate both downgrades and upgrades in sovereign debt ratings with drops in stock liquidity.

A third link between rating changes and stock liquidity can be present through an information channel, similarly to Odders-White and Ready (2006), who find that low credit ratings are related to large adverse selection, and hence to low liquidity in U.S. stocks. Since credit rating agencies update the sovereign credit ratings based on their evaluations of various economic and political factors of the security and the country, a sovereign credit rating change can deliver important new information about a country, lowering information asymmetry and thus, enhancing liquidity. While both upgrade and downgrade announcements are informational events, however, there could be an asymmetric impact of rating changes on the stock market between upgrades and downgrades. That is, rating agencies are in general reluctant to give downgrades (Becker and Milbourn, 2011), hence, downgrades may contain more information than upgrades, implying that downgrades may have a bigger impact on liquidity than upgrades. Furthermore, the larger the magnitude of credit rating changes, the bigger the impact on stock liquidity. However, an upgrade is often considered as containing less of new information than a downgrade, or even no news. As a result, the impact of an upgrade on liquidity will be limited. Therefore, the asymmetric information channel in general posits that sovereign debt rating changes may improve liquidity, and the effect of a sovereign debt downgrade should be larger than that of an upgrade.

We investigate the cross-firm and cross-country variations in the impact of sovereign rating changes, including changes in credit outlook, on stock liquidity. We employ a regression framework instead of the popular event-study framework in order to avoid potential misleading interpretations of the results that may arise from event clustering (Gande and Parsley, 2005). Our results show that sovereign rating changes have a significant impact on stock liquidity, and that larger events have greater effects than smaller events. Moreover, we find that the effect is asymmetric, in that it is significant for downgrades but not for upgrades, and that the loss of sovereign investment grade has a particularly strong negative impact on stock liquidity. Overall, our empirical results provide support for the funding constraints hypothesis, but not for the portfolio rebalancing hypothesis or for the information channel hypothesis.

The empirical tests to examine how the transmission of the externality due to a rating change is affected by its interaction with different firm-level characteristics, show that firms with higher degree of ownership concentration, lower liquidity level, or lower turnover, tend to experience more negative liquidity effects from sovereign debt rating changes. Firms with higher return on asset appear to experience less negative liquidity effects from sovereign debt rating changes. And the impact from downgrades is in general stronger than from upgrades.

At the country level, the legal and macroeconomic environment of a country is important in explaining the differences in the impact of sovereign credit rating changes on stock liquidity across countries. Specifically, stocks from a country with civil law, lower stock market capitalization, lower credibility of financial disclosure, higher risk of outright confiscation, or higher foreign institutional ownership are conducive of a larger liquidity dry-up in sovereign debt rating change events.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 presents the data and the empirical methodology. Section 4 discusses the empirical results, and Section 5 concludes the paper.

2. Literature review

Our work borrows from two related strands of literature: studies on liquidity, in particular on the effect of market-wide events on stock liquidity, and research on the effect of changes in sovereign credit risk conditions on the private sector.

The concept that market declines reduce asset liquidity has received growing attention in the theoretical and empirical literature. Many models predict that a large market decline increases the demand for liquidity as agents liquidate their positions across assets, and that it reduces the supply of liquidity as liquidity providers hit their wealth or funding constraints. These setups include the collateral-based models of Brunnermeier and Pedersen (2009), Anshuman and Viswanathan (2005), Garleanu and Pedersen (2007), and Gromb and Vayanos (2002); the limit-to-arbitrage model by Kyle and Xiong (2001); and the coordination failure models by Bernardo and Welch (2004), Morris and Shin (2004), and Vayanos (2004), among others. Consistent with the theoretical literature on financial constraints and liquidity dry-ups, Hameed et al. (2010) and Karolyi et al. (2012) find that negative market returns decrease stock liquidity, especially during times of tightness in the funding market.

Huang and Stoll (2001) study the impact of exchange rates on a firm's value through the effect on the liquidity of the firm's equity shares. They focus on the behavior of American Depositary Receipts (ADRs) from the United Kingdom and Mexico around two major exchange rate crises — the pound sterling withdrawal from the European Exchange Rate Mechanism in September 1992 and the Mexican peso devaluation of December 1994. They argue that exchange rate variability can increase the bid–ask spread of a firm's stock and other measures of execution costs, and via this route affect the firm's cost of capital and firm value. This analysis is of great interest because of the growing literature on the effect of liquidity on firm value. Amihud and Mendelson (1986) present the first piece of evidence to support the hypothesis that asset liquidity is priced in equilibrium, followed by supporting evidence such as Amihud and Mendelson (1989), Brennan and Subrahmanyam (1996), Datar et al. (1998), Brennan et al. (1998), Easley et al. (2002), Acharya and Pedersen (2005), Lee (2011) and Kim and Lee (2014).

The literature that systematically examines the impact of sovereign credit ratings mainly focuses on the effect of debt ratings on the instruments being rated. For instance, Cantor and Packer (1996) and Larraín et al. (1997) find a significant effect on bond yield spreads following rating changes. More recent studies explore the effect of sovereign ratings on private sector's debt ratings and interest rates. In this vein, Borensztein et al. (2007), and Cavallo and Valenzuela (2010) document the presence of a "sovereign ceiling lite", whereby private sector debt ratings tend to be below the sovereign's debt rating, especially in emerging markets where asymmetric information problems are more severe. Borensztein et al. (2007) highlight three channels through which the creditworthiness of the government may affect that of the private sector: first, the negative impact that a sovereign default has on the domestic economy as a whole, which broadly undermines the financial strength of the private sector; second, a spillover effect from the insolvency of the sovereign to private debtors. A sovereign debt that is very close to default may adopt measures that can directly affect the private sector's ability to repay its obligations, such as resorting to inflationary financing or large tax increases; and third, the imposition of direct capital controls or other administrative measures that effectively prevent private borrowers from servicing their external obligations when the sovereign reaches a situation of default or near default. On account of the imposition of capital controls, the private sector always defaults on its external obligations when the sovereign defaults, which provides a rationale for a sovereign ceiling.

Ferri et al. (2001) and Ferri and Liu (2002) empirically study the impact of sovereign ratings on private debt ratings directly. In particular, the latter paper estimates the impact of sovereign ratings on firms' credit ratings and firm-level financial indicators. They find that sovereign ratings have a significant effect on private ratings in emerging market economies, but the effect on firm-level variables, which are specified as a weighted average aggregate, is statistically insignificant. While these studies explore firm-level implications of sovereign rating changes, none of them explores the link between sovereign rating changes and stock liquidity.

3. Data and empirical methodology

We collect data on sovereign bond rating changes on long-term foreign currency debt from January 1990 to December 2009. We use rating changes from Standard & Poor's (S&P) because S&P is more active than other rating agencies in making rating changes, and their changes tend to be unanticipated by the market and to precede changes made by other rating agencies (Brooks et al., 2004; Gande and Parsley, 2005).

The numerical scale of the credit ratings is shown in the Appendix. To capture meaningful changes in ratings, we define the overall numerical scale of rating as the sum of numeric value of alphabetical ratings and that of credit outlook. An event is defined as a non-zero change in the overall numerical rating scale. We use the numerical conversion of credit ratings similar to those in Gande and Parsley (2010) and Correa et al. (2013), with a slight variant in the numeric scale for *outlook* changes. We assign a value of zero to the Stable and Watch Developing outlook status because Watch Developing only implies that there may be a change in the credit rating in the future and that the rating agency is reviewing it, but it does not indicate directionality. Hence, it is not positive or negative news, and as a result we should not assign it a positive or negative value. The Global Credit Portal Ratings Direct by Standard & Poor's (August 7, 2007) shows that Watch Negative is more frequently followed by downgrades than just Outlook Negative. The document describes Watch Negative as corresponding to a nearer term and higher probability of a default event relative to an Outlook Negative. Hence, Watch Negative is assigned a more negative value than Outlook Negative. We assign −0.6 to Watch Negative and −0.3 to Outlook Negative. We do not have any events associated to Watch Positive in our sample, and we assign 0.6 to Outlook Positive.[2]

We calculate daily stock returns using the daily total return index from Datastream for all stocks from 40 countries for the period from January 1, 1990 to December 31, 2009.[3] Out of the 40 countries, 14 countries are developed markets (Australia, Hong Kong, Japan (Developed Asia); Belgium, Canada, Denmark, Finland, Ireland, Italy, New Zealand, Norway, Spain, Sweden, and the UK (Developed Europe/Canada)) and the other 26 countries are emerging markets (Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela (Latin America); China, India, Indonesia, Malaysia, Pakistan, Philippines, South Korea, Sri Lanka, Taiwan, Thailand (Emerging Asia); Czech Republic, Greece, Hungary, Israel, Poland, Portugal, Russia, South Africa, and Turkey (Emerging Europe/Middle East/Africa)).[4] The following data are also obtained from Datastream: the global market return index, trading volume, and foreign exchange rates from WM/Reuters.[5]

For a stock to be included in our sample, it must have market capitalization data at the end of the year prior to the event year, together with previous year-end book-to-market ratio. We choose only stocks that are traded on the major exchanges.[6] We use only common stocks and exclude stocks with special features such as Depository Receipts (DRs), Real Estate Investment Trusts (REITs), and preferred stocks.[7,8]

We do not eliminate stocks that did not survive until the end of the sample in order to avoid survivorship bias. Similar to Ince and Porter (2006), we set the daily return as missing if any

2 Our use of different numeric values for outlook that are different from those of Gande and Parsley can also be justified by considering the following example. In Brazil, the foreign currency rating of long-term bond was changed to BB+/Positive on May 16, 2007, which was the most recent day when the rating change was made before April, 30, 2008, when the rating was BBB-/Stable. According to Gande and Parsley (2010), on May 16, 2007, the numeric value of rating is 12, which is the sum of 11 (BB+) and 1 (positive outlook). However, on April 30, 2008, the value is also 12 (BBB-) since the numeric scale of outlook is zero (Stable). Hence, the actual event of change in ratings (from BB+ to BBB-) is unduly not captured as an event, and as a result, the event date of April 30, 2008 will be dropped from the sample. We find that this is not the only such case in our sample. Our new numeric values of outlook fix this problem and correctly identify the rating changes event.

3 The return index for each stock is built under the assumption that dividends are re-invested. It is also adjusted for stock-splits.

4 The categorization of a country into a developed market or an emerging market follows the definition of the International Finance Corporation (IFC) of the World Bank Group.

5 Since the exchange rates against the U.S. dollar do not cover all the sample periods for some countries but the rates against the U.K. sterling do, the U.S. dollar exchange rates are calculated by using the cross-rates through the pound sterling.

6 All countries have one major exchange except China (Shanghai and Shenzhen stock exchanges) and Japan (Osaka and Tokyo stock exchanges).

7 The exclusion of stocks with special features is performed manually by examining the names of the securities, given that Datastream/Worldscope does not provide any code for discerning such stocks from common stocks. Some examples of 'name filters' are as follows. In Belgium, shares of the types AFV and VVPR (the types are named by Datastream/Worldscope) are dropped since they have preferential dividends or tax incentives. In Canada, income trusts are excluded by deleting stocks with names that include "INC.FD". In Mexico, shares of the types ACP and BCP are removed since they have the special feature of being convertible into series A and B shares, respectively, after one year. In Italy, RSP shares are dropped due to their non-voting provisions.

8 Worldscope usually tracks one share for each firm and it is mostly the PN share in Brazil. Although PN shares are preferred stocks, they are not excluded in Brazil since they account for the majority of stocks in that country.

Table 1
Number of events by country and region.

Country	No. of events	No. of positive events	No. of negative events	No. of big positive events	No. of big negative events	No. of events (inv to non-inv)	No. of events (non-inv to inv)	No. of stock-event days	Avg. rating	Max. rating	Min. rating
ARGENTINA	21	7	14	1	1	0	0	55	6.6	10.0	0.0
AUSTRALIA	4	4	0	0	0	0	0	104	19.9	21.0	18.7
BELGIUM	1	0	1	0	0	0	0	16	20.1	20.6	20.0
BRAZIL	13	11	2	0	0	0	1	696	9.2	12.0	7.6
CANADA	4	2	2	0	0	0	0	747	20.5	21.0	19.7
CHILE	6	6	0	0	0	0	0	42	15.3	17.0	13.0
CHINA	2	2	0	0	0	0	0	54	14.2	17.0	13.0
COLOMBIA	4	3	1	0	0	0	0	15	11.1	12.6	9.7
CZECH	3	2	1	0	0	0	0	21	15.3	16.0	13.6
DENMARK	3	3	0	0	0	0	0	167	20.5	21.0	19.0
FINLAND	8	6	2	0	0	0	0	172	20.1	21.0	18.0
GREECE	13	5	8	1	0	0	0	664	14.2	17.0	12.0
HONG KONG	15	11	4	0	0	0	0	298	17.0	20.0	15.4
HUNGARY	16	8	8	0	0	0	1	194	13.2	15.0	10.7
INDIA	13	7	6	0	0	0	1	1174	10.9	13.0	9.7
INDONESIA	1	0	1	0	0	0	0	4	8.5	13.0	0.0
IRELAND	4	1	3	0	0	0	0	36	19.7	21.0	18.0
ISRAEL	9	6	3	0	0	0	0	415	14.5	16.6	11.7
ITALY	9	1	8	0	0	0	0	546	18.7	20.6	17.0
JAPAN	7	3	4	0	0	0	0	7855	19.9	21.0	17.7
MALAYSIA	19	11	8	0	1	0	0	153	15.2	17.6	11.7
MEXICO	10	5	5	0	0	0	0	35	11.7	14.0	9.7
NEW ZEALAND	5	4	1	0	0	0	0	7	19.5	20.0	18.0
NORWAY	1	1	0	0	0	0	0	25	21.0	21.0	20.7
PAKISTAN	14	4	10	0	2	0	0	38	6.6	8.6	0.0
PERU	5	5	0	0	0	0	1	10	10.2	12.0	9.0
PHILIPPINES	13	6	7	0	0	0	0	41	10.0	11.6	8.7
POLAND	13	9	4	0	0	0	1	751	13.7	15.6	10.6
PORTUGAL	9	4	5	0	0	0	0	115	18.1	19.0	16.6
RUSSIA	16	13	3	1	0	0	1	220	9.1	14.6	0.0
S.AFRICA	7	5	2	0	0	0	1	222	12.4	14.0	10.6
S.KOREA	16	10	6	1	3	1	1	3394	15.8	18.0	7.4
SPAIN	8	4	4	0	0	0	0	597	20.0	21.0	19.0
SRI LANKA	2	0	2	0	0	0	0	2	7.6	8.0	6.7
SWEDEN	6	3	3	0	0	0	0	442	20.5	21.0	19.7
TAIWAN	7	2	5	0	0	0	0	39	19.1	20.0	17.7
THAILAND	11	5	6	0	0	0	0	92	13.9	16.0	11.7
TURKEY	34	16	18	0	2	1	0	799	8.4	13.0	5.4
UK	1	0	1	0	0	0	0	790	21.0	21.0	20.7
VENEZUELA	15	6	9	1	0	0	0	29	7.9	10.6	0.0
Sum	368	201	167	5	9	2	8	21,076			
DEVELOPED	76	43	33	0	0	0	0	11,802	19.9	21.0	15.4
EMERGING	292	158	134	5	9	2	8	9274	12.4	20.0	0.0
Developed Asia	26	18	8	0	0	0	0	8257	19.0	21.0	15.4
Developed Europe/Canada	50	25	25	0	0	0	0	3545	20.1	21.0	17.0
Emerging Asia	98	47	51	1	6	1	2	4991	12.9	20.0	0.0
Emerging Europe/Middle East	120	68	52	2	2	1	4	3401	13.5	19.0	0.0
Latin America	74	43	31	2	1	0	2	882	10.3	17.0	0.0

This table reports the number of sovereign rating changes (events) by country and region for 1990:01–2009:12. Events are decomposed to each of the following: positive (upgrade), negative (downgrade), big-positive (upgrade by 2 or more numeric scales), big-negative (downgrade by 2 or more numeric scales), investment grade to non-investment grade, and non-investment grade to investment grade. The next column displays the total stock-event days for each country. The last three columns show the average rating, the maximum rating, and the minimum rating of a country over the sample period.

daily return above 100% (inclusive) is reversed the following day.[9] The daily return is set to missing if either the total return index for the previous day or that of the current day is less than 0.01. We compute returns based on the U.S. dollar. As in Lesmond (2005) and Lee (2011), we mark a day as a non-trading day if more than 90% of the stocks in a given exchange have zero returns on that day. We drop stocks whose previous year-end prices are below \$5 (in US dollar) in order to avoid possible biases caused by including too many small stocks.[10] To improve the precision of illiquidity measure, we drop a stock-month observation if the total number of zero-volume days is more than 80% in a given month, as in Lee (2011).

Table 1 reports the number of events, the number of stock-day observations and other descriptive statistics for individual countries in the upper panel, and for various regions in the lower panel. To examine asymmetric effects of rating changes, we decompose events into positive (upgrade), negative (downgrade), big-positive (upgrade by 2 or more numeric scales), and big-negative (downgrade by 2 or more numeric scales) events.

From the upper panel, we see that Turkey experienced rating changes most frequently (34 times), followed by Argentina (21 times), and Malaysia (19 times). Five countries experienced big-positive events, while five encountered big-negative events in the sample. We also observe that two countries (South Korea and

[9] Specifically, the daily returns for both days *t* and *t-1* are set to missing if $R_{i,t}R_{i,t-1} \leq 1.5$, where $R_{i,\,t}$ and $R_{i,t-1}$ are the gross returns for day *t* and *t-1*, respectively, and if at least one of the two is 2 or greater.

[10] Our results remain robust when we use the \$2 cutoff price to screen the sample.

Turkey) experienced a sovereign rating change from investable grade to non-investable grade, while eight countries (Brazil, Hungary, India, Peru, Poland, Russia, South Africa, and South Korea) encountered an upgrade from non-investment grade to investment grade.

We can see from the bottom panel of Table 1 that emerging economies experienced 292 rating changes, which account for 79% of the total events in our sample, while the developed countries encountered 76 sovereign debt rating changes, which account for 21% of the sample. The average rating is far lower in emerging economies than in developed economies. Furthermore, there is a much larger variation in the ratings among emerging economies than among developed countries. In the developed economies group, about two thirds of the events occurred in Europe/Canada and one third occurred in Asia. In the emerging markets, the events are more evenly distributed across the three geographical regions.

We use a turnover-based Amihud measure to measure illiquidity. Specifically, the illiquidity for stock i on day t is defined as the adjusted absolute return of the stock divided by its daily turnover, namely:

$$RV_{i,t} = \frac{\left|\hat{r}_{i,t}\right|}{TV_{i,t}}. \tag{1}$$

where:

$TV_{i,t} = \frac{VO_{i,t}}{NSH_{i,y-1}}$, daily turnover for stock i at date t;
$VO_{i,\,t}$: daily trading volume for stock i at date t;
$NSH_{i,y-1}$: the number of shares outstanding for stock i at the end of the previous year;
$\hat{r}_{i,t}$: adjusted return for stock i at date t.

Notice that we use this turnover-based Amihud measure as opposed to Amihud's (2002) original measure of illiquidity, which uses a dollar trading volume instead of TV in the denominator, because the dollar trading volume can be tainted by market capitalization, as pointed out by Brennan et al. (2013). It is important to note that the Amihud's measures of illiquidity used for events, both the original and the turnover-based one, may be biased due to potential endogeneity because the return component may be contaminated by information rather than liquidity following an event. To overcome this problem, we use an instrumental variable regression in which we regress returns on the intercept and daily turnover, which is related to order flow but not to information/fundamentals, and then use the fitted values of this regression, $\hat{r}_{i,t}$, in Eq. (1) to replace the raw return. We use this adjusted, or turnover-based, Amihud measure instead of the original Amihud measure in all the analyses in this paper.[11]

We take the natural logarithm of the adjusted Amihud measure and denote the result as

$$\log RV_{i,t} = \log\left(1 + RV_{i,t}\right). \tag{2}$$

The validity of the Amihud measure as an illiquidity proxy is demonstrated in the prior literature (e.g., Goyenko et al., 2009). One additional benefit of using this measure is that we can construct illiquidity measures at the daily frequency. Moreover, the Amihud measure is quite intuitive and closely follows the concept of price impact of Kyle (1985).

As shown in Chordia et al. (2005), Hameed et al. (2010), and Karolyi et al. (2012), time-series of illiquidity shows significant day-of-the-week effect together with monthly effect. Hence, we run the following time-series filtering regression for each of the stocks over the sample period, using a similar methodology to Hameed et al. (2010) and Karolyi et al. (2012)[12,13]:

$$\log RV_{i,t} = \sum_{k=1}^{4} \beta_i^{D,k} DDum_{k,t} + \sum_{k=1}^{11} \beta_i^{M,k} MDum_{k,t} + \beta_i^{H} HolDum_t + \beta_i^{Y1} Year1_t + \beta_i^{Y2} Year2_t + ILLIQ_{i,t} \tag{3}$$

In Eq. (3), $DDum_k$ (k= 1,…,4) is a day-of-the-week dummy variable, $MDum_k$ (k = 1, …, 11) is a monthly dummy; *HolDum* is a dummy variable constructed as followings: if a non-trading day falls on a Friday, then the preceding Thursday has a value of one; if a non-trading day falls on a Monday, then the succeeding Tuesday has a value of one; if a non-trading day falls on a Tuesday, Wednesday, or Thursday, then both the preceding and succeeding trading days have a value of one; and *Year1* and *Year2* are used to filter the time trend of illiquidity. *Year1* (*Year2*) is defined as the difference between the current calendar year and 1990 (2000) or the beginning trading year of stock i, whichever comes later. The intercept is included as part of the residual term, $ILLIQ_{i,t}$.

Table 2 displays the cross-sectional means of the coefficient estimates of Eq. (3) together with the t-statistics for testing whether the mean coefficients are different from zero across stocks. It also shows the proportion of significant positive or negative coefficients.

We see that all but two coefficients in Eq. (3) are on average significantly different from zero at the 5% significance level. The day-of-the-week effect is significant for a large proportion of the stocks in the sample. For example, the coefficient of the Monday dummy is positive for 75% of the sample stocks and 30% of the stocks have a positive and significant (at the 10% level) coefficient on the same variable. The monthly dummies and the holiday dummy, *HolDum*, are also significant for a great proportion of stocks, implying that monthly seasonality and holiday effects of liquidity exist in the time series, consistent with Chordia et al. (2005).

Using the residuals from regression Eq. (3), we compute the first difference of *ILLIQ*:

$$\Delta ILLIQ_i(t-1, t+1) = ILLIQ_{i,t+1} - ILLIQ_{i,t-1} \tag{4}$$

This denotes the change in illiquidity between day t – 1 and t + 1 and will be used as the dependent variable in our subsequent regression analysis.[14]

Table 3 reports descriptive statistics of sample firms on event dates by country and region. The numbers are averages across stock-event day observations.

We observe from Panel A that the average daily stock returns range from –2.93% (China) to 7.52% (Indonesia) across countries.[15]

[11] Our conclusions are robust to regressing returns on dollar trading volume instead of on turnover volume, and using the fitted values from this first stage regression. Our results are also robust to using Amihud's (2002) original dollar trading volume-based measure with fitted values from any of the two first-stage regressions.

[12] We perform the main analyses based on the changes in *raw* illiquidity, which is in Eq. (2), without applying Eq. (3), and obtained stronger results. This shows that our results are not driven by the regression in Eq (3), which simply aims to remove the seasonal component of illiquidity measure.

[13] An alternative method suggested by a reviewer is to estimate rolling regressions of (3) as follows: for each stock at day t, we run the filtering regression (3) from the beginning of the sample to day t and use the parameters to estimate illiquidity at day t+1 and calculate the residual for day t+1. We then run the regression using observations upto day t+1 to estimate the residual for period t+2. We do this rolling estimation for the residuals t+2, t+3, etc. We have also used parameters estimated using observations at t to calculate the residual for day t+2 (2 periods ahead). To examine whether our findings are robust to this choice for de-seasonalizing the data, we have also used this approach. Our results are indeed robust to using this alternative liquidity estimation method.

[14] If event occurs on non-trading day, we compute the first difference using the values from the trading days that are closest to the event date.

[15] One may ask why a developed country that has experienced almost only downgrades (e.g. Italy) has its event return in the top tercile of its return distribution,

Table 2
Coefficients of filtering regressions.

	Mon.	Tue.	Wed.	Thu.	Year1	Year2
Mean	0.04	0.00	0.00	0.00	−0.01	−0.01
t-stat	(44.68)	(4.98)	(−0.24)	(2.67)	(−3.51)	(−3.97)
% pos	74.78	53.42	50.30	51.55	47.91	36.13
% pos & abs(t)> 1.64	30.32	11.99	8.70	8.03	39.62	31.45
% neg	25.22	46.58	49.70	48.45	52.09	63.87
% neg & abs(t)> 1.64	2.54	8.78	6.98	5.41	43.15	59.06
Total #	6415	6415	6415	6415	4308	5984
	Jan.	**Feb.**	**Mar.**	**Apr.**	**May**	**Jun.**
Mean	0.01	0.01	−0.01	0.01	0.00	0.02
t-stat	(2.35)	(1.99)	(−2.41)	(2.41)	(−0.92)	(6.15)
% pos	49.07	46.76	41.02	45.80	45.42	48.21
% pos & abs(t)> 1.64	19.10	18.84	17.24	20.65	19.02	22.27
% neg	50.93	53.24	58.98	54.20	54.58	51.79
% neg & abs(t)> 1.64	20.05	23.42	30.74	27.79	26.86	25.16
Total #	6413	6412	6411	6412	6415	6412
	Jul.	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**HolDum**
Mean	0.06	0.08	0.04	0.02	0.02	0.04
t-stat	(20.40)	(27.28)	(14.43)	(10.41)	(9.73)	(27.37)
% pos	56.86	64.30	52.57	52.43	51.10	69.15
% pos & abs(t)> 1.64	30.36	35.92	24.23	22.09	17.21	25.45
% neg	43.14	35.70	47.43	47.57	48.90	30.85
% neg & abs(t)> 1.64	18.56	13.74	20.08	19.27	16.24	3.01
Total #	6412	6411	6410	6409	6409	6311
Adj R^2 of first stage regression = 0.02			Adj R^2 of second stage regression = 0.14			

The first row of this table reports average coefficient across sample stocks from the following filtering regression:

$$\log RV_{i,t} = \sum_{k=1}^{4} \beta_i^{D,k} DDum_{k,t} + \sum_{k=1}^{11} \beta_i^{M,k} MDum_{k,t} + \beta_i^{H} HolDum_t + \beta_i^{Y1} Year1_t + \beta_i^{Y2} Year2_t + ILLIQ_{i,t}$$

where $DDum_k$ (k= 1,…,4) is a day-of-the-week dummy variable, $MDum_k$ ($k = 1, \ldots, 11$) is a monthly dummy; *HolDum* is a dummy variable constructed as followings: if a non-trading day falls on a Friday, then the preceding Thursday has a value of one; if a non-trading day falls on a Monday, then the succeeding Tuesday has a value of one; if a non-trading day falls on a Tuesday, Wednesday, or Thursday, then both the preceding and succeeding trading days have a value of one; and *Year1* and *Year2* are used to filter the time trend of illiquidity. *Year1* (*Year2*) is defined as the difference between the current calendar year and 1990 (2000) or the beginning trading year of stock *i*, whichever comes later. The second row displays the *t*-statistic for testing whether the mean coefficient is different from zero across stocks. "% pos" ("pos & abs(t)> 1.64") shows the percentage of stocks whose coefficient estimate is positive (and its absolute *t*-statistic is greater than 1.64). "% neg" ("neg & abs(t)> 1.64") shows the percentage of stocks whose coefficient estimate is negative (and its absolute *t*-statistic is greater than 1.64). The last row shows the number of stocks.

The relatively large absolute values for average returns imply that stocks across countries were exposed to large impact of sovereign rating changes. The average RV shows substantial variation across countries in our stock-event day sample. Generally, RV is higher for emerging market countries than in developed market countries. The fourth column shows that the changes in illiquidity between day $t-1$ and $t+1$ vary from −0.58 (Indonesia) to 1.37 (New Zealand).

while the event return of a country (e.g. South Korea) with twice as many upgrades as downgrades is in the bottom quartile of its distribution and has the most negative event return in the sample. Even on aggregate, Developed Asia has more than twice as many positive as negative events, developed Europe has more negative than positive. Developed Asia has a negative average event return. Developed Europe has a positive event return. These statistics do not result from an outlier problem though. In an unreported exercise, we examine the summary statistics for the stock market *index* returns for these countries/regions. This exercise is based on the raw data directly downloaded from the Datastream database (hence no screening is made on our side). They are statistics for the entire stock market indices and are free from outlier issues. For example, while Italy has 1 positive event and 8 negative events, its average market index return for the 8 negative events is *positive* 0.37% which is higher than its market index return for the positive event (0.03%). This makes Italy's market index return 0.33% for all events. Similarly, while South Korea has more positive events than negative events, its average market index return for the positive events is 0.52%, but its average market index return for the negative events is −5.43%. This produces an average market index return of −1.71% for all event days for South Korea. A similar pattern is also observed for the two aggregate regions. What this exercise shows can be summarized as follows. First, the stock returns do not necessarily become negative (positive) on downgrade (upgrade) events. The sign may depend on how surprising the event is relative to the market's expectation. Second, the impact of rating changes on return may be asymmetric and nonlinear. That is, the impact of one big downgrade could be much stronger than that of multiple small changes in ratings. In sum, there is no reason to believe that the numbers in our tables are affected by outliers.

There also exist substantial variations in the summary statistics across regions and across country groups, as can be seen from Panels B and C in Table 3. The panels show that on an event day, emerging market countries are more illiquid and more volatile in general.

It is interesting to see the relation between ratings level and illiquidity. Tables 1 and 3 provide an opportunity to check whether a higher level of rating is related to a lower level of illiquidity. We compute the correlation between average illiquidity (values of "*logRV*" in Table 3) and average ratings (from Table 1). The correlation is −0.52, supporting our conjecture that a lower sovereign credit rating level is related to a higher level of illiquidity of stocks.

4. Empirical results

4.1. Rating changes and liquidity

In this paper, following Gande and Parsley (2005), we use the regression approach using only event-related observations as opposed to the traditional event study approach to conduct our analysis because our regression approach is adequate to avoid the potential event window contamination problem due to events clustering. When events occur irregularly, unlike earnings announcements, it is possible that the events are clustered and the most popular way of handling this event clustering is to take only the first events in a given event windows. Unfortunately, given the well-known highly clustered feature of sovereign rating changes events (Gande and Parsley, 2005), we cannot take only the first event in our study. That is, we consider *all* events because

Table 3
Descriptive statistics.

Country	Return (%) (1)	logRV (2)	ILLIQ (3)	$\Delta ILLIQ_i$ $(t-1, t+1)$ (4)	Stdev (5)	$\log(MV)_{y-1}$ (6)	$\log(B/M)_{y-1}$ (7)	Return (%) on event (+) (8)	$\Delta ILLIQ_i$ $(t-1, t+1)$ on event (+) (9)	Return (%) on event (−) (10)	$\Delta ILLIQ_i$ $(t-1, t+1)$ on event (−) (11)
					Panel A. by country						
ARGENTINA	−0.64	3.17	1.80	0.00	0.03	7.15	−1.09	0.99	0.21	−1.90	−0.16
AUSTRALIA	−0.80	2.44	0.66	0.04	0.02	6.69	−0.75	−0.80	0.04		
BELGIUM	0.35	2.83	1.10	0.11	0.01	6.61	−0.32			0.35	0.11
BRAZIL	2.63	2.70	1.13	−0.04	0.03	6.67	−0.64	2.94	−0.04	−0.41	−0.03
CANADA	0.93	2.97	1.04	0.02	0.02	6.25	−0.64	1.48	−0.02	0.03	0.09
CHILE	0.39	2.92	2.11	−0.12	0.01	7.47	−0.69	0.39	−0.12		
CHINA	−2.93	2.17	1.09	−0.18	0.04	8.13	−2.52	−2.93	−0.18		
COLOMBIA	0.68	2.87	1.76	−0.25	0.02	7.43	−0.19	0.75	−0.31	−0.36	0.64
CZECH	−0.91	3.08	0.93	0.21	0.03	6.66	−0.26	−0.18	0.05	−1.46	0.33
DENMARK	0.62	2.84	0.94	0.06	0.02	5.41	−0.64	0.62	0.06		
FINLAND	0.59	2.91	0.95	0.03	0.02	6.37	−0.85	0.60	0.05	0.33	−0.47
GREECE	−1.16	3.07	0.95	−0.09	0.03	5.54	−1.09	−1.72	−0.05	−0.67	−0.13
HONG KONG	−0.14	2.17	0.83	0.08	0.02	7.11	−0.45	0.47	0.01	−1.36	0.23
HUNGARY	−1.77	2.88	1.00	0.00	0.03	5.28	−0.49	0.12	−0.05	−4.09	0.05
INDIA	−0.36	3.32	1.62	0.01	0.03	6.14	−1.26	−0.15	0.01	−0.91	0.03
INDONESIA	7.52	3.88	1.39	−0.58	0.05	6.99	−0.54			7.52	−0.58
IRELAND	−1.12	3.16	1.59	0.22	0.04	7.36	−0.95	−0.30	0.24	−1.64	0.21
ISRAEL	0.07	2.73	1.59	−0.03	0.03	5.99	−0.75	0.13	−0.08	−0.04	0.06
ITALY	0.40	1.98	0.86	0.04	0.02	6.65	−0.64	−0.16	0.14	0.47	0.03
JAPAN	−0.35	2.28	0.85	0.01	0.02	6.25	−0.57	−0.69	0.01	0.18	0.00
MALAYSIA	−2.13	2.91	1.21	−0.04	0.04	6.04	−1.60	0.20	−0.09	−3.51	−0.01
MEXICO	1.36	2.44	0.67	0.08	0.03	7.82	−0.80	1.14	−0.07	1.72	0.33
NEW ZEALAND	−0.40	2.66	0.64	1.37	0.01	5.52	−0.74	−0.19	0.85	−1.60	4.53
NORWAY	−1.00	2.78	0.99	0.02	0.03	5.46	−1.47	−1.00	0.02		
PAKISTAN	−0.50	4.04	2.32	0.06	0.02	5.70	−1.42	1.25	0.14	−0.96	0.04
PERU	0.73	4.13	2.70	0.01	0.03	5.13	−0.48	0.73	0.01		
PHILIPPINES	0.15	3.22	1.84	−0.05	0.02	7.36	−0.83	0.48	−0.24	−0.31	0.22
POLAND	0.07	3.40	1.37	−0.01	0.03	5.24	−0.85	1.00	−0.03	−1.57	0.03
PORTUGAL	−0.65	2.89	1.41	0.11	0.02	5.81	−0.57	−0.37	0.16	−0.99	0.05
RUSSIA	5.37	5.40	4.02	−0.15	0.05	7.74	−0.68	0.98	−0.08	9.61	−0.23
S.AFRICA	−1.31	3.15	1.36	0.08	0.03	7.49	−1.03	0.65	0.05	−3.74	0.12
S.KOREA	−2.39	2.03	0.63	0.03	0.05	4.90	0.25	0.14	−0.02	−5.87	0.10
SPAIN	−0.34	2.81	0.91	−0.06	0.02	6.90	−0.72	0.54	−0.10	−1.36	−0.02
SRI LANKA	−0.50	1.93	1.19	−0.03	0.05	1.46	2.74			−0.50	−0.03
SWEDEN	0.24	2.61	0.70	0.06	0.03	5.75	−0.90	0.51	0.10	−0.59	−0.08
TAIWAN	1.11	1.38	0.55	0.00	0.03	7.05	−1.45	0.98	−0.14	1.26	0.14
THAILAND	−1.29	2.90	1.28	0.09	0.04	5.59	−0.94	0.27	0.06	−3.16	0.12
TURKEY	0.83	2.99	1.05	−0.01	0.04	5.47	−1.18	2.90	−0.11	−0.99	0.08
UK	−1.01	0.34	0.11	0.01	0.05	5.13	−0.02			−1.01	0.01
VENEZUELA	−0.20	4.16	2.23	−0.44	0.04	5.94	−0.54	−0.04	−0.42	−0.29	−0.45
					Panel B. by developed vs. emerging						
DEVELOPED	−0.23	2.24	0.82	0.01	0.02	6.21	−0.57	−0.32	0.01	−0.12	0.01
EMERGING	−0.73	2.74	1.12	0.00	0.04	5.76	−0.65	0.58	−0.03	−2.74	0.04
					Panel C. by region						
Developed Asia	−0.35	2.28	0.85	0.01	0.02	6.29	−0.57	−0.65	0.01	0.13	0.01
Developed Europe/Canada	0.05	2.15	0.74	0.02	0.03	6.04	−0.56	0.77	0.02	−0.52	0.02
Emerging Asia	−1.82	2.40	0.92	0.02	0.04	5.50	−0.45	0.02	−0.02	−4.65	0.08
Emerging Europe/Middle East	0.13	3.22	1.39	−0.03	0.03	5.81	−0.91	0.68	−0.05	−0.52	0.00
Latin America	2.12	2.80	1.26	−0.05	0.03	6.75	−0.65	2.57	−0.05	−0.54	−0.08

This table reports averages across stock-event days by country and region of daily returns (based on the U.S. dollar), log of illiquidity measure (logRV), the residual from the filtering regression of Eq. (1) (*ILLIQ*), changes in illiquidity between day *t*-1 and $t+1$, $\Delta ILLIQ_i(t-1, t+1)$, standard deviation of returns, market capitalization one year prior to the event, and book-to-market ratio one year prior to the event.

sometimes subsequent sovereign rating changes after the first event could be even larger in magnitude and could have a higher impact than the first. Therefore, we cannot just take the first event and ignore the subsequent events over the benchmark time period used in the event study approach. Moreover, the event study framework recognizes the existence of events in a particular point in time but does not distinguish the differences in the "degree" or severity among events in many cases. In our study, large changes in ratings should be distinguished from small changes in ratings since the impact of large and small events may be quite different (and this is what we show in our paper later). We believe that the regression approach is the more appropriate methodology to study the issues in our paper and, hence, the results are based on the regression approach.

Using changes in illiquidity in Eq. (4), we run the following regression to estimate the impact of sovereign rating changes on stock liquidity:

$$\Delta ILLIQ_{c,i}(t-1, t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 R_{m,t} + \beta_3 \log(MV)_{i,y-1} + \beta_4 \log(B/M)_{i,y-1} + \beta_5 Stdev_{i,t-30,t-1} + \beta_6 \log RV_{i,y-1} + other\,controls + \varepsilon_{c,i,t} \quad (5)$$

where $Event_{c,\,t}$ is defined as the change in *absolute* value of numeric sovereign ratings. The subscripts *c, i, y* and *t* denote, respectively, country, stock, year, and event date.

We include control variables that have been shown or expected to be associated with liquidity, namely, global market return, $R_{m,\,t}$; the log of previous year-end market capitalization in U.S. dollars, $\log(MV)_{i,y-1}$; and the log of previous year-end book-to-market ratio, $\log(B/M)_{i,y-1}$. According to Chordia et al. (2007), *B/M* is a proxy for firm visibility, which is significantly related to trading volume (turnover). We use the standard deviation of the past 30-day daily returns, $Stdev_{i,t-30,t-1}$, to control for volatility, because

Table 4
Regression of change in illiquidity over [−1, +1] on events.

	Intercept (1)	Event (2)	Event (+) (3)	Event (−) (4)	Global market return R_m (5)	log(MV) (6)	log(B/M) (7)	Stdev (8)	logRV (9)	Adj R^2 (%) (10)	No. of obs. (11)
(1)	−0.035	0.066***								0.83	21,071
	(−0.63)	(5.94)									
(2)	−0.068	0.064***			−1.758					0.96	21,071
	(−1.25)	(6.36)			(−1.57)						
(3)	−0.167***	0.047***			−1.617	0.012***	0.001	1.617***	−0.015	1.14	20,875
	(−2.83)	(4.26)			(−1.52)	(3.11)	(0.17)	(3.11)	(−1.02)		
(4)	−0.029		0.024	0.074***						0.86	21,071
	(−0.51)		(1.28)	(5.82)							
(5)	−0.062		0.021	0.072***	−1.769					0.99	21,071
	(−1.10)		(1.39)	(6.28)	(−1.59)						
(6)	−0.157**		0.013	0.055***	−1.629	0.012***	0.001	1.543***	−0.015	1.16	20,875
	(−2.47)		(0.74)	(4.11)	(−1.54)	(2.82)	(0.10)	(2.83)	(−1.03)		

This table reports results from the following regressions:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 R_{m,t} + \beta_3 \log(MV)_{i,y-1} + \beta_4 \log(B/M)_{i,y-1} + \beta_5 Stdev_{i,t-30,t-1} + \beta_6 \log RV_{i,y-1} + other\ controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^{+}_{c,t} + \beta_2 Event^{-}_{c,t} + controls + \varepsilon_{c,i,t}$$

Event is the absolute value of a numeric change of sovereign ratings; *Event*$^+$ (*Event*$^-$) is the absolute value of a rating change if the change is positive (negative), and zero otherwise; R_m is the daily return computed from Datastream's global market index; *log(MV)* is the log of the prior year-end market capitalization in U.S. dollars; *log(B/M)* is the log of prior year-end book-to-market ratio; *Stdev* is the standard deviation of the past 30-day daily returns; *logRV* is the log of (1+prior year average RV); and *No. of obs.* is the number of stock-day observations. Each regression also contains country and year dummies. Numbers in parentheses are *t*-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

volatility may affect the cost of inventory holdings (Stoll, 2000). To control for the effect of the illiquidity level on the changes in liquidity, we include the log of (1+average RV) of the previous year, $\log RV_{i,y-1}$, in the regression. We also use country and year dummies as additional control variables in the regression.

Sovereign downgrades may have a different effect on liquidity than upgrades. Hence, we separate upgrades (positive events) from downgrades (negative events) and run the following regression:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^{+}_{c,t} + \beta_2 Event^{-}_{c,t} + controls + \varepsilon_{c,i,t} \quad (6)$$

where *Event*$^+$ (*Event*$^-$) is defined as the *absolute* value of rating changes if the rating change is positive (negative), and zero otherwise.

Estimation results of Eq. (5) are reported in Rows (1) (3) of Table 4, where each row displays the regression results with a different set of control variables. Although our sample has only 40 clusters (by having 40 countries), and is highly unbalanced across countries, in Table 4 and in all subsequent tables, we adopt the most conservative approach to estimate the standard errors and cluster them at the country-level. In this way we account for the possibility that each stock's response to the sovereign credit rating event might not be independent.

We find from Table 4 that the coefficient of the *Event* variable, which treats positive and negative events in the same way, is found to be positively significant at the 1% level, regardless of the type of the control variables used in the regression. We also see that market capitalization and standard deviation of past 30-day returns are significantly positively associated with stock illiquidity at the 1% level, while the other three control variables are not statistically significant. These results imply that sovereign credit rating changes significantly reduce stock liquidity.

Rows (4)–(6) of Table 4 present estimation results of Eq. (6) with events separated into positive (upgrade) and negative (downgrade) ones. We find a clear asymmetry between the results for positive ratings events and those for negative events, as measured by both the parameter values and their associated *t*-statistics. The coefficient for the negative rating events has the expected positive sign and is statistically significant at the 1% level for all three regressions, indicating that sovereign credit downgrades significantly reduce stock liquidity. However, positive events are insignificant, and their coefficient estimates are much smaller in magnitude than those for negative events. The results in Rows (4)–(6) of Table 4 suggest that sovereign downgrades are generally more informative about changes in stock liquidity than upgrades. These findings are robust to different variables used as controls in the regression. Overall, our empirical evidence lends support to the funding constraint hypothesis, but not to the information channel hypothesis. The significant and positive coefficients for downgrading events are also consistent with the portfolio rebalancing hypothesis. However, the asymmetric impact of downgrades and upgrades, as shown by the insignificant coefficient for upgrades, is not consistent with the portfolio rebalancing hypothesis.

4.2. Nonlinear effect of sovereign credit rating changes on liquidity

It is possible that large changes in sovereign bond ratings have larger effects on stock liquidity than small rating changes. Furthermore, since institutional investors usually hold securities rated above a certain threshold to maintain the specified risk level for the fund, large upgrades and downgrades of sovereign debt will change the pool of market participants, and thus can sharply affect stock liquidity. Moreover, these effects can extend beyond the participants of the sovereign debt market. The presence of a "sovereign ceiling lite" implies that one country's sovereign debt downgrades can lead to downgrades of the private debt of that country. Kaminsky and Schmukler (2002) point out that, as a result of loss of investment grade status in sovereign debt, most domestic corporations are unable to tap into international credit markets and commercial banks are unable to issue internationally recognized letters of credit for domestic exporters and importers, thereby isolating the economy from international capital markets. Hence, it is reasonable to expect a *nonlinear* response in stock liquidity to large sovereign debt rating changes.

To investigate this nonlinear effect of rating changes on liquidity, we split events to four groups based on event size: large upgrade, small upgrade, large downgrade and small downgrade. Our regression is specified as follows:

Table 5
Regression of changes in illiquidity over [−1,+1] on extreme events.

	Event (big+) (1)	Event (small+) (2)	Event (big-)(3)	Event (small-) (4)	Event (inv to non-inv) (5)	Event (non-inv to inv) (6)	Adj R^2 (%) (7)	No. of obs. (8)
(1)	0.008	0.000	0.057***	0.034			1.15	20,875
	(0.44)	(0.01)	(4.93)	(0.98)				
(2)					0.151***		1.10	20,875
					(3.12)			
(3)						0.028	1.06	20,875
						(0.41)		

This table reports results from the following regressions:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t}^{Big+} + \beta_2 Event_{c,t}^{Small+} + \beta_3 Event_{c,t}^{Big-} + \beta_4 Event_{c,t}^{Small-} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_i(t-1,t+1) = \alpha + \beta Event_{c,t}^{INV\to NONINV} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_i(t-1,t+1) = \alpha + \beta Event_{c,t}^{NONINV\to INV} + controls + \varepsilon_{c,i,t}$$

where $Event^{Big+}$ ($Event^{Big-}$) is defined as the absolute value of an upgrade (downgrade) if the change in rating is greater than or equal to 2, and zero otherwise; $Event^{Small+}$ ($Event^{Small-}$) is the absolute value of an upgrade (downgrade) if the change is less than 2, and zero otherwise; $Event^{INV->N\circ NINV}$ is a dummy variable whose value is one if rating changes from investable to non-investable grade, and zero otherwise; and $Event^{N\circ NINV->INV}$ is a dummy variable equal to one for a rating upgrade from non-investable to investable grade, and zero otherwise. Each regression is run with the full set of control variables along with country and year dummies. The parameter estimates of the control variables are not reported to save space. Numbers in parentheses are *t*-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t}^{Big+} + \beta_2 Event_{c,t}^{Small+} + \beta_3 Event_{c,t}^{Big-} + \beta_4 Event_{c,t}^{Small-} + controls + \varepsilon_{c,i,t} \quad (7)$$

where $Event^{Big+}$ ($Event^{Big-}$) is defined as the absolute value of an upgrade (downgrade) if the change in rating is greater than or equal to 2, and zero otherwise. $Event^{Small+}$ ($Event^{Small-}$) is the absolute value of an upgrade (downgrade) if the change is less than 2, and zero otherwise.

We also hypothesize that rating changes from investment grade to non-investment grade or vice versa may have a large effect on liquidity. Hence, we run the following regressions:

$$\Delta ILLIQ_i(t-1,t+1) = \alpha + \beta Event_{c,t}^{INV\to NONINV} + controls + \varepsilon_{c,i,t} \quad (8)$$

$$\Delta ILLIQ_i(t-1,t+1) = \alpha + \beta Event_{c,t}^{NONINV\to INV} + controls + \varepsilon_{c,i,t} \quad (9)$$

where $Event^{INV->N\circ NINV}$ is a dummy variable whose value is one if rating changes from investable grade to non-investable grade, and zero otherwise. $Event^{N\circ NINV->INV}$ is a dummy variable that equals to one for a rating upgrade from non-investable grade to investable grade, and zero otherwise.

Eqs. (7)–(9) are run with the same sets of control variables used in Table 4, along with country and year dummies. Our results are robust to the different sets of control variables, so in order to economize on space, we only report the regressions using the full set of control variables.

Table 5 reports the results of Regressions (7)–(9), where parameter estimates of all the control variables are omitted for brevity. The result in Row (1) of Table 5 shows that a negative event with a large magnitude, $Event^{Big-}$, exhibits a significant impact on stock liquidity at the 1% level, whereas the impact of a small negative event is not significant and has a smaller magnitude. The effect of a positive event is insignificant.

Table 1 shows that we have more positive events (201) than negative events (167). This implies that rating agencies are in general reluctant to give downgrades (Becker and Milbourn, 2011), thus, negative rating changes, once issued, are more informative than positive ones. This helps explain the statistical significance and larger magnitude of the coefficients associated with negative events. In addition, large downgrade events can induce exclusion of firms from the credit market, thereby reducing the ability of these firms to reveal information. These findings are consistent with the explanations based on the funding constraints and the portfolio rebalancing incentives. However, the evidence does not support the information asymmetry argument. Positive events, on the contrary, are often not considered informational events and therefore their impact is statistically insignificant.

Row (2) of Table 5 shows that when sovereign debt is downgraded from investable to non-investable status, stock liquidity decreases significantly at the 1% level. From Row (3), we find that a sovereign rating change from non-investment grade to investment grade does not significantly affect stock liquidity.

In sum, Table 5 demonstrates that a large downgrade of sovereign debt significantly reduces stock liquidity, while a small event does not. Conceivably, when the rating change is small in magnitude, the effect of reduced information asymmetry will be small and can be offset by the information contained in the direction of the rating change itself. A large downgrade though, significantly decreases stock liquidity. While the portfolio rebalancing motive is an important driver behind the large drop in liquidity following big negative events, the results also lend support to the funding constraint channel. We also find that a sovereign downgrade from investable to non-investable status significantly reduces stock liquidity. However, the effect is not symmetric in that a sovereign debt upgrade from non-investable to investable status does not significantly impact stock liquidity.

4.3. Cross-firm differences of effect on liquidity

In this subsection, we investigate how the effects of sovereign credit rating changes vary across different firm characteristics. To that end, we modify our regression specification by including interaction terms of events with firm characteristics as follows:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 Char_i \cdot Event_{c,t} + controls + \varepsilon_{c,i,t} \quad (10)$$

where *Char* denotes a firm-specific characteristic. To allow for a non-linear effect of firm characteristic, we use the rank of a firm characteristic instead of its numerical value, namely, *Char* in Eq. (10) is a rank of stocks whose value is 1 (low/small), 2, or 3 (high/big) based on the rank of its characteristic among all stocks in a given country. We employ the following firm characteristics in our analysis: market capitalization, book-to-market ratio, degree of ownership concentration (*Closely-Held Shares*), liability to assets ratio, average level of illiquidity, average turnover, return on asset (*ROA*), and the number of analyst recommendations, all measured

Table 6
Regression of changes in illiquidity over [−1,+1] on events interacted with firm characteristics.

	Firm characteristic (Char) (1)	Event (2)	Event *Char (3)	Event (+) (4)	Event (+) *Char (5)	Event (−) (6)	Event (−) *Char (7)	Adj R^2 (%) (8)	No. of obs. (9)
(1)	Market cap	0.025	0.010					1.14	20,875
		(0.81)	(0.61)						
				0.007	0.003	0.024	0.014	1.16	20,875
				(0.21)	(0.22)	(0.73)	(0.76)		
(2)	Book-to-market	0.033*	0.007					1.14	20,875
		(1.72)	(1.17)						
				−0.006	0.011	0.045**	0.005	1.15	20,875
				(−0.22)	(0.87)	(2.05)	(0.84)		
(3)	Closely-held Shares (%)	0.011	0.019***					1.41	15,710
		(0.61)	(2.98)						
				−0.013	0.007	0.010	0.024***	1.45	15,710
				(−0.33)	(0.47)	(0.59)	(4.50)		
(4)	Liability/Assets	0.069***	−0.010					1.14	20,633
		(3.37)	(−1.56)						
				0.033	−0.010	0.075**	−0.009	1.16	20,633
				(1.14)	(−0.82)	(2.21)	(−0.77)		
(5)	Illiquidity	0.000	0.025***					1.17	20,875
		(0.03)	(3.84)						
				0.033	−0.013	−0.013	0.036***	1.22	20,875
				(1.33)	(−1.20)	(−0.88)	(8.34)		
(6)	Turnover	0.082**	−0.019					0.97	19,810
		(2.19)	(−1.19)						
				−0.016	0.013	0.121***	−0.034**	1.03	19,810
				(−0.53)	(0.98)	(3.09)	(−2.23)		
(7)	ROA	0.060**	−0.006					1.12	19,538
		(2.46)	(−0.69)						
				−0.004	0.009	0.086***	−0.015*	1.15	19,538
				(−0.14)	(0.58)	(3.61)	(−1.82)		
(8)	N Analyst recommendation	0.054***	−0.006					1.33	16,418
		(4.62)	(−0.65)						
				0.015	−0.003	0.060***	−0.006	1.34	16,418
				(0.38)	(−0.24)	(3.98)	(−0.53)		
(9)	Politically-connected	0.048***	−0.001					1.13	20,788
		(4.42)	(−0.03)						
				0.011	0.018	0.056***	−0.004	1.14	20,788
				(0.62)	(0.63)	(4.30)	(−0.06)		

This table reports results from the following regressions

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 Char_i \cdot Event_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^+_{c,t} + \beta_2 Char_i \cdot Event^+_{c,t} + \beta_3 Event^-_{c,t} + \beta_4 Char_i \cdot Event^-_{c,t} + controls + \varepsilon_{c,i,t}$$

Event is the absolute value of a numeric change of sovereign ratings. $Event^+$ ($Event^-$) is the absolute value of a rating change if the change is positive (negative), and zero otherwise. *Char* is the rank of a stock, which takes a value of 1(low/small), 2, or 3(high/big) based on the rank of its characteristic among stocks in a given country. The firm characteristics employed in our analysis include: market capitalization, book-to-market ratio, degree of concentration of ownership (*Closely-Held Shares*), liability to assets ratio, average illiquidity (*RV*), average turnover, return on asset (*ROA*), and number of analyst recommendations, all measured one year prior to the event. Politically-connected is a dummy variable equal to 1 if the firm has a political connection and zero otherwise. Each regression is run with the full set of control variables along with country and year dummies. The parameter estimates of the control variables are not reported to save space. Numbers in parentheses are *t*-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

at the end of the year or over the year prior to the event. We also distinguish between politically-connected firms from those that have no political connection, using a dummy variable equal to one if the firm has a political connection and zero otherwise. We obtain the list of politically-connected firms used in Faccio (2006), and merge that list with our sample firms. We collect the annual data of closely held shares as percentage of total number of common shares outstanding from Datastream/Worldscope. The data on the number of analyst recommendations are from the I/B/E/S dataset. Each regression is run with the full set of control variables along with country and year dummies. The parameter estimates of the control variables are not reported to save space.

Table 6 reports our estimation results. Column (3) shows that firms with higher degree of ownership concentration or lower liquidity experience a significant liquidity drop from a sovereign debt rating change.

As shown in the previous sections, downgrades can have a different effect on liquidity than upgrades. Hence, we separate upgrades (positive events) from downgrades (negative events) and run the following regression:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^+_{c,t} + \beta_2 Char_i \cdot Event^+_{c,t} + \beta_3 Event^-_{c,t} + \beta_4 Char_i \cdot Event^-_{c,t} + controls + \varepsilon_{c,i,t} \quad (11)$$

Results reported in Columns (4)–(7) of Table 6 indicate that the effects of sovereign rating changes interacted with firm characteristics primarily come from downgrades. We find that negative events interacting with higher degree of ownership concentration and average illiquidity level significantly reduces stock liquidity. Furthermore, we find negative events interacting with the average turnover ratio to be significantly negative at the 5% level, and negative events interacting with ROA to be significantly negative at the 10% level.

The results for the negative events interacted with firm characteristics are generally well in accordance with economic intuition. Stocks with a higher fraction of closely-held shares are more difficult to rebalance due to shortage of free-floating shares, leading to more decline in liquidity following a sovereign debt downgrade. Smaller or more illiquid stocks experience stronger funding constraints upon sovereign downgrades, resulting in lower liquidity. Stocks with a higher average turnover ratio face looser funding constraints following sovereign downgrades, and thus their liquidity will not drop as much. Stocks with a higher return on asset have a higher profit margin. They can better handle shocks and thus following sovereign downgrades, their liquidity will not fall as much.

4.4. Cross-country differences of effect on liquidity

We further explore how the transmission of the externality is affected by its interaction with different country characteristics. To that end, we run the following regression:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 CountryVar_i \cdot Event_{c,t} + controls + \varepsilon_{c,i,t} \quad (12)$$

where *CountryVar* denotes a country-level characteristic. The country-level characteristics that we employ in our analysis are described as follows: *LAW* is a dummy variable equal to one if the stock is from a civil law country, and zero if it is from a common law country; *ANTIDIRR* is an index of minority investor protection with a higher value indicating stronger protection; *ANTIDIRR* (Spamann) is the modified *ANTIDIRR* index proposed by Spamann (2010); *EXPRISK* is a measure of threat of outright confiscation or forced nationalization with a higher value indicating a lower risk; and *ACCSTAND* is an index of accounting standard with a higher value indicating a higher accounting standard. The above four variables are previously used in La Porta et al. (1998). We use the following additional variables: *SCAP* is the average of stock market capitalization to GDP ratio over 1988–1999 (Stulz, 2005); *DISCL* is an index of credibility of financial disclosure (Bushman et al., 2004); *EARNMGT* is an aggregate earnings management score with a higher value indicating a higher level of earnings management (Leuza et al., 2003); *NANALYSTS* is the number of analysts for the largest 30 firms in a country (Bushman et al., 2004); *Foreign inst ownership* is foreign institutional ownership (Ferreira and Matos, 2008); and *GDP per capita* is in 2003 U.S. dollars, which is obtained from World Development Indicator.

Each regression is run with the full set of control variables along with year dummies. Table 7 reports the estimation results. As can be seen from Column (3), the *LAW* variable carries a significant positive sign, indicating that across countries, the impact of a sovereign debt rating changes on stock liquidity is stronger for firms in a country with civil law than that for firms in a country with common law. The coefficient of the *DISCL* variable is significantly negative at the 1% level, implying that the impact of sovereign debt rating changes on stock liquidity is weaker for firms in a country with higher credibility of financial disclosure.

To investigate differential effects, we separate upgrades (positive events) from downgrades (negative events) and run the following regression:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^{+}_{c,t} + \beta_2 CountryVar_i \cdot Event^{+}_{c,t} + \beta_3 Event^{-}_{c,t} + \beta_4 CountryVar_i \cdot Event^{-}_{c,t} + controls + \varepsilon_{c,i,t} \quad (13)$$

We report results in Columns (4)–(7) of Table 7. We find the positive events interacting with the *LAW* variable to be statistically significant, implying that following an upgrade in sovereign debt, firms in a country with civil law will increase liquidity by less than those in a country with common law.

The negative coefficients of interaction term with the market cap variable *SCAP* shows that the impact of sovereign debt rating upgrade on stock liquidity is weaker in a country with a larger average stock market capitalization. Intuitively, stocks in countries with well-developed stock market (as measured by a large *SCAP*) have less liquidity constraint or less information asymmetry.

The significant negative coefficients of the interaction terms with the *DISCL* variable indicate that the impact of sovereign debt rating changes on stock liquidity is less severe for firms in a country with higher credibility of financial disclosure. Intuitively, for a country with high transparency, revision in expectations from new information delivered by rating changes is relatively small either because expectations are less sensitive to new information in a transparent environment or because the events add little information.

The significant negative coefficient of the interaction term with the *EXPRISK* variable suggests that the effect of a sovereign debt rating changes on stock liquidity is weaker for firms in a country with lower risk of outright confiscation or forced nationalization.

Finally, the significant positive coefficient of the interaction term with the foreign institutional ownership variable indicates that the impact of a sovereign debt downgrade on stock liquidity is stronger in a country with a higher foreign institutional ownership.

4.5. Robustness

In this sub-section, we report more results to check for robustness of our findings. First, we investigate the exposure of stock liquidity in each country to a world liquidity factor. In the previous sections, we have used the global market return, $R_{m,\,t}$, to control for the global factor in all regressions. Lee (2011) finds that an aggregate liquidity factor can affect stock returns around the world, and it is the U.S. market illiquidity, not the global market illiquidity, that significantly impacts individual stock returns. Following Lee (2011), we estimate the daily U.S. market aggregate illiquidity by computing an equally-weighted average of stock illiquidity (also using the adjusted Amihud measure) in the U.S. and we use the change of log of (1 +U.S. market illiquidity) over the [−1,+ 1] interval. This aggregate market illiquidity measure is denoted by$\Delta ILLIQ_{US}(t-1,t+1)$. We replace the global market return, $R_{m,\,t}$, by the market illiquidity factor, $\Delta ILLIQ_{US}(t-1,t+1)$, and re-run the previous regressions (5)–(9).

Estimation results are reported in Table 8. The insignificant parameters on the changes in the US market illiquidity presented in Column (11) show that individual stock liquidity is not significantly exposed to the U.S. aggregate market liquidity. Comparing with the previous results reported in Table 4 (Rows (3) and (6)) and Table 5, our basic conclusions regarding the effects of sovereign debt rating changes on stock liquidity remain unchanged.

Second, we check whether our results are robust to the length of the event window. To that end, we compute the changes in stock liquidity over the longer event windows of [−2,+ 2] and [−5,+ 5]. We run Regressions (5) and (6) with various sets of control variables with this longer event window and report the estimation results in Table 9.

Panel A of Table 9 shows similar results to those reported in Table 4. That is, the coefficients on *Event* and *Event*− are all significant at the 1% level, though the magnitude and the *t*-values are smaller than those in Table 4, even when all the control variables are included.

Rows (1)–(2) of panel B of Table 9 show that the coefficient of the *Event* variable is positive and statistically significant, consistent with those in our baseline case reported in Table 4, only when other firm-level control variables are not included. In rows (3)-(4) of panel B, we also find that the coefficient of the positive events and negative events is significant at the 10% level only when firm-level control variables are excluded in the regressions. These results are in general weaker than those reported in Table 4, implying that the impact of sovereign rating changes are absorbed by the market rather quickly.

For further robustness check, we repeat all regressions only with the change in illiquidity over the day of the rating change, i.e., over [−1,0]. If a rating change itself is an informational event that may reduce information asymmetry, liquidity may improve right

Table 7
Regression of change in illiquidity over [−1,+1] on events interacted with country-specific variables.

	Country specific variable (CV) (1)	Event (2)	Event* CV (3)	Event (+) (4)	Event (+)* CV (5)	Event (−) (6)	Event (−)* CV (7)	No. of obs. (8)	Adj R^2 (%) (9)
(1)	LAW	−0.088*	0.140**					19,831	0.75
	(0 = common, 1 = civil law)	(−1.70)	(2.67)						
				−0.116**	0.129**	0.006	0.056	19,831	0.83
				(−2.28)	(2.40)	(0.06)	(0.61)		
(2)	ANTIDIRR	0.080*	−0.014					19,825	0.74
		(1.82)	(−0.82)						
				0.034	−0.016	0.107**	−0.021	19,825	0.79
				(0.71)	(−0.85)	(2.07)	(−1.00)		
(3)	ANTIDIRR	−0.121	0.040					19,825	0.68
	(Spamann)	(−0.74)	(0.97)						
				−0.029	0.006	−0.029	0.020	19,825	0.71
				(−0.18)	(0.15)	(−0.13)	(0.36)		
(4)	EXPRISK	0.247	−0.024					19,831	0.73
		(1.59)	(−1.33)						
				0.315*	−0.038*	0.427**	−0.044*	19,831	0.79
				(1.94)	(−1.95)	(1.96)	(−1.77)		
(5)	ACCSTAND	0.220	−0.003					19,751	0.71
		(1.16)	(−0.94)						
				0.244	−0.004	0.412	−0.006	19,751	0.79
				(1.44)	(−1.48)	(1.38)	(−1.21)		
(6)	SCAP	0.083***	−0.080					19,291	0.75
		(2.71)	(−1.31)						
				0.047	−0.112*	0.109***	−0.114	19,291	0.81
				(1.52)	(−1.75)	(2.81)	(−1.52)		
(7)	DISCL	0.217***	−0.002***					19,827	0.82
		(3.68)	(−2.85)						
				0.190**	−0.003**	0.286***	−0.003***	19,827	0.87
				(2.42)	(−2.30)	(3.71)	(−3.01)		
(8)	EARNMGT	−0.062	0.004					17,728	0.71
		(−0.83)	(1.46)						
				−0.107	0.004	−0.069	0.005	17,728	0.75
				(−1.40)	(1.50)	(−0.58)	(1.02)		
(9)	NANALYSTS	0.007	0.004					19,827	0.69
		(0.09)	(0.51)						
				−0.023	0.002	0.062	−0.001	19,827	0.73
				(−0.29)	(0.30)	(0.65)	(−0.09)		
(10)	Foreign inst ownership	−0.098	0.012					14,719	0.56
	(% of market cap)	(−1.27)	(1.52)						
				−0.051	0.007	−0.182**	0.022**	14,719	0.58
				(−0.38)	(0.54)	(−2.00)	(2.05)		
(11)	GDP per capita (in 2003 U.S. dollars)	0.038	0.000					21,071	0.74
		(1.10)	(−0.24)						
				0.000	0.000	0.063	0.000	21,071	0.78
				(−0.00)	(−0.45)	(1.56)	(−0.77)		

This table reports results from the following regressions:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1\, Event_{c,t} + \beta_2\, CountryVar_i \cdot Event_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1\, Event^{+}_{c,t} + \beta_2\, CountryVar_i \cdot Event^{+}_{c,t} + \beta_3\, Event^{-}_{c,t} + \beta_4 CountryVar_i \cdot Event^{-}_{c,t} + controls + \varepsilon_{c,i,t}$$

where *Event* is the absolute value of a numeric change of sovereign ratings; $Event^{+}$ ($Event^{-}$) is the absolute value of a rating change if the change is positive (negative), and zero otherwise; *LAW* is a dummy variable equal to one if the stock is from a civil law country, and zero if it is from a common law country; *ANTIDIRR* is an index of minority investor protection with a higher value indicating stronger protection; *EXPRISK* is a measure of political risk with a higher value indicating a lower risk; *ACCSTAND* is an index of accounting standard with a higher value indicating a higher accounting standard; *SCAP* is the average of stock market capitalization to GDP ratio over 1988–1999; *DISCL* is an index of accounting standard; *EARNMGT* is an aggregate earnings management score with a higher value indicating a higher level of earnings management; *NANALYSTS* is the number of analysts covered for the largest 30 firms in a country; *Foreign inst ownership* is foreign institutional ownership; and *GDP per capita* is in 2003 U.S. dollars. Each regression is run with the full set of control variables along with year dummies. The parameter estimates of the control variables are not reported to save space. Numbers in parentheses are *t*-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

after the announcement is made, so that the change can be captured by the window of [−1,0]. We find that the *Event* and *Event (−)* variables are generally insignificant except for the case when the full set of control variables are used, the case in which they are negative and significant only at the 10% level. With such weak evidence for [−1,0], it is difficult to draw a solid conclusion that the announcement itself is an informational event, These result are also not reported to save space.

As we revealed in the footnote in Section 3, our results remain robust when we use $2 cutoff price to screen the sample.

Lastly, and maybe most importantly, we performed all the analyses with the original Amihud measure with fitted values from both the regressions of stock return on dollar volume and on turnover volume. We also repeated all the analyses based on turnover-based Amihud measure with fitted values from the regression of return on dollar volume. Our results are similar in all cases.

5. Conclusion

Sovereign rating changes affect stock liquidity. We examine the presence of such externality using data for a panel of stocks from 40 countries over the last two decades and find that sovereign rating changes have a significant impact on stock liquidity. Large changes in sovereign ratings have stronger effects on equity liquidity than small changes. Furthermore, the effect is asymmetric,

Table 8
Regression of changes in illiquidity over [−1,+1] on events after controlling for U.S. market liquidity.

	Intercept (1)	Event (2)	Event (+) (3)	Event (−) (4)	Event (big+) (5)	Event (big-) (6)	Event (small+) (7)	Event (small-) (8)	Event (inv to noninv) (9)	Event (noninv to inv) (10)	$\Delta ILLIQ_{US}$ (11)	log (MV) (12)	log (B/M) (13)	Stdev (14)	logRV (15)	Adj R^2 (%) (16)	No. of obs. (17)
(1)	−0.149**	0.052***									−0.007	0.007***	0.005	1.449***	−0.018	1.00	19,869
	(−2.11)	(3.65)									(−0.03)	(2.65)	(0.72)	(2.96)	(−1.27)		
(2)	−0.146**		0.017	0.059***							0.028	0.007**	0.004	1.369***	−0.018	1.02	19,869
	(−2.01)		(0.79)	(3.81)							(0.13)	(2.40)	(0.63)	(2.69)	(−1.27)		
(3)	−0.145**				0.004	0.062***	0.021	0.046			0.045	0.007**	0.004	1.347***	−0.017	1.02	19,869
	(−2.02)				(0.21)	(4.85)	(0.37)	(0.91)			(0.18)	(2.41)	(0.64)	(2.63)	(−1.24)		
(4)	−0.144**								0.149***		0.084	0.008***	0.005	1.635***	−0.017	0.96	19,869
	(−1.97)								(2.64)		(0.50)	(2.69)	(0.78)	(3.62)	(−1.20)		
(5)	−0.137*									0.049	0.227	0.008***	0.005	1.740***	−0.017	0.92	19,869
	(−1.95)									(0.70)	(1.22)	(2.76)	(0.80)	(3.63)	(−1.20)		

This table reports results from the following regressions:

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event_{c,t} + \beta_2 \Delta ILLIQ_{US}(t-1,t+1) + \beta_3 \log(MV)_{i,y-1} + \beta_4 \log(B/M)_{i,y-1} + \beta_5 Stdev_{i,t-30,t-1} + \beta_6 \log RV_{i,y-1} + other\ controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^{+}_{c,t} + \beta_2 Event^{-}_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-1,t+1) = \alpha + \beta_1 Event^{Big+}_{c,t} + \beta_2 Event^{Small+}_{c,t} + \beta_3 Event^{Big-}_{c,t} + \beta_4 Event^{Small-}_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{i}(t-1,t+1) = \alpha + \beta\, Event^{INV\rightarrow NONINV}_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{i}(t-1,t+1) = \alpha + \beta\, Event^{NONINV\rightarrow INV}_{c,t} + controls + \varepsilon_{c,i,t},$$

$\Delta ILLIQ_{US}(t-1,t+1)$ is the change in U.S. market liquidity, and all other variables are defined the same way as in the previous tables. Each regression also contains country and year dummies. Numbers in parentheses are t-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

Table 9
Regression of changes in illiquidity over [−5,+5] on events.

	Intercept	Event	Event (+)	Event (−)	Global market return, R_m	log(MV)	log(B/M)	Stdev	logRV	Adj R^2 (%)	No. of obs.
					Panel A. Event windows of [−2,+2]						
(1)	−0.086*	0.048***			0.128					0.746	20,387
	(−1.70)	(2.85)			(0.21)						
(2)	−0.091	0.040**			0.164	−0.002	−0.011	0.908**	−0.021	0.840	20,207
	(−1.33)	(2.34)			(0.26)	(−0.62)	(−1.02)	(2.47)	(−1.17)		
(3)	−0.083*		0.022	0.053***	0.125					0.755	20,387
	(−1.69)		(0.64)	(3.23)	(0.20)						
(4)	−0.085		0.016	0.045**	0.160	−0.003	−0.011	0.861**	−0.021	0.847	20,207
	(−1.28)		(0.48)	(2.60)	(0.25)	(−0.75)	(−1.05)	(2.39)	(−1.18)		
					Panel B. Event windows of [−5,+5]						
(1)	0.169***	0.061**			−0.104					0.894	19,502
	(2.99)	(2.13)			(−0.36)						
(2)	0.206***	0.045			−0.060	−0.011*	−0.007	1.164**	0.001	0.942	19,344
	(3.08)	(1.59)			(−0.21)	(−1.94)	(−0.67)	(2.47)	(0.04)		
(3)	0.169***		0.068*	0.058*	−0.096					0.890	19,502
	(2.97)		(1.91)	(1.86)	(−0.35)						
(4)	0.206***		0.046	0.045	−0.059	−0.011*	−0.007	1.165**	0.001	0.937	19,344
	(3.07)		(1.23)	(1.57)	(−0.22)	(−1.96)	(−0.67)	(2.57)	(0.04)		

This table reports results from the following regressions:

$$\Delta ILLIQ_{c,i}(t-k,t+k) = \alpha + \beta_1 Event_{c,t} + controls + \varepsilon_{c,i,t}$$

$$\Delta ILLIQ_{c,i}(t-k,t+k) = \alpha + \beta_1 Event^{+}_{c,t} + \beta_2 Event^{-}_{c,t} + controls + \varepsilon_{c,i,t},$$

$\Delta ILLIQ_{c,i}(t-k,t+k)$ is the change in liquidity for stock i over the [t-k,t+k] interval and all other variables are defined the same way as in the previous tables. Each regression also contains country and year dummies. Numbers in parentheses are t-statistics based on standard errors clustered at the country level. The asterisks *, **, and *** denote significance at 10, 5, and 1% levels, respectively.

in that the impact is much stronger for downgrades than for upgrades. The loss of sovereign investment grade status has a particularly strong negative impact on stock liquidity. Overall, our findings lend support to the funding constraints hypothesis in that a binding funding constraint, which is triggered by sovereign rating downgrade, is the channel through which the unfavorable rating changes lead to deterioration in stock liquidity. These results are robust after controlling for country- and firm-specific factors.

In focusing on the implications of changes in public debt conditions on stock liquidity, our study highlights an additional transmission channel through which the management of public debt affects the private sector. In addition, our work explores how the transmission of the externality is affected by its interaction with different firm-level and country-specific characteristics.

At the firm level, we find that in response to a negative sovereign credit event, firms with higher concentration of ownership or lower liquidity level tend to experience more significant negative liquidity effects, while firms with higher turnover ratio or higher return on assets tend to experience significantly smaller decreases in stock liquidity following a sovereign downgrade.

At the country level, on the one hand, higher stock market capitalization relative to GDP, higher credibility of financial disclosure, and lower risk of outright confiscation or forced nationalization are country-level factors that lessen the impact of a sovereign debt downgrade on stock liquidity. On the other hand, civil law origin and higher foreign institutional ownership are country-specific factors that exacerbate the decline in stock liquidity when sovereign debt undergoes a credit rating change.

Appendix. Numerical scales of credit ratings

This table presents numerical scales of S&P sovereign bond ratings together with credit outlook. The overall numerical value of a credit rating is the sum of numeric value for the sovereign rating and that for credit outlook.

Sovereign bond rating	Numeric
AAA	21
AA+	20
AA	19
AA−	18
A+	17
A	16
A−	15
BBB+	14
BBB	13
BBB−	12
BB+	11
BB	10
BB−	9
B+	8
B	7
B−	6
CCC+	5
CCC	4
CCC−	3
CC	2
C	1
SD,D	0
Outlook	**Numeric**
Positive	0.6
Stable, Watch developing	0
Negative	−0.3
Watch negative	−0.6

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