Online Appendix to "Regulation and Market Liquidity"

A Brief History of the Volcker Rule

In this section, we discuss the rulemaking process of the Volcker Rule as a most salient example of post-crisis financial regulations to illustrate the empirical challenges that we need to address in this study.

The Volcker Rule refers to Section 619 Title VI of the 2010 Dodd-Frank Act, originally proposed by former Federal Reserve Chairman Paul Volcker to restrict U.S. banks from proprietary trading and investing in hedge funds and private equities. As a long-time skeptic of financial innovation, Volcker argued that such speculative activity played a central role in the financial crisis of 2008--2009.

The Volcker Rule first appeared in a January 2009 Group of Thirty Report, but was not embraced at the time (Krawiec and Liu, 2015). Influential members of the Obama Administration, including former Treasury Secretory Timothy Geithner and Director of the National Economic Council Larry Summers, actively opposed the Volcker Rule, which they believed to be overly restrictive for banks. As a result, the Volcker Rule was not even part of the initial financial reform legislation proposed by the Treasury Department[1].

Throughout the summer and fall of 2009, the initial Treasury proposal was hammered by critics as one catering to Wall Street. As discontent brewed, the Obama administration started to shift towards Paul Volcker's proposal (Skeel, 2010). On January 21, 2010, President Obama, with Paul Volcker by his side, publicly announced his support for the rule. On July 21, 2010, the Volcker Rule, together with other provisions of the Dodd-Frank Act, was signed into law.

Like many other provisions of the Dodd-Frank Act, the Volcker Rule was highly incomplete when the legislation was passed. The specific rulemaking was delegated to five federal agencies, including the Federal Reserve Board, FDIC, OCC, CFTC and SEC. Given the substantial incompleteness of the legislative statute, the rulemaking process ignited a heated debate among regulators and industry special interest groups: over 17,000 public comments were filed. Big banks such as Bank of America, Goldman Sachs, and JP Morgan expressed concerns about the rule. Conservative politicians such as the Chairman of the House Financial Services Committee, Representative Spencer Bachus, vowed to limit the effect of the Volcker Rule[2]. Industry lobbyists were also pushing for loosening the restrictions or extending the compliance deadlines.

Due to all the above controversies, the implementation of the Rule was delayed multiple times. Congress originally mandated that the Volcker Rule become effective in July 2012, two years after Dodd-Frank passed. However, during his report to Congress on February 29, 2012, Federal Reserve Chairman Ben Bernanke said that the central bank and other regulators would not meet that deadline. After missing the first deadline, regulators estimated that the rule would be finished during the first few months of 2013. Again, this second deadline was missed. On December 10, 2013, all five of the necessary regulatory agencies approved a version of the Volcker Rule which had a longer compliance period and fewer metrics than earlier proposals[3]. However, the approval was immediately followed by an emergency lawsuit filed by the American Bankers Association, bringing the five regulatory agencies back to the reviewing process. On January 14, 2014, revised

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[1] Department of The Treasury, Financial Regulatory Reform: A New Foundation: Rebuilding Financial Supervision and Regulation (2009), available at http://www.treasury.gov/initiatives/Documents/FinalReport_web.pdf.

[2] See "Bachus Urges Regulators Not to Rigidly Implement Volcker Rule", by Deborah Solomon, The Wall Street Journal, November 4, 2010

[3] See "Volcker Shrugged", PwC Financial Services Regulatory Practice, December, 2013.

final regulations were approved by all five regulatory agencies. The effective date was set on April 1, 2014 and the deadline of conformance was extended to July 21, 2015. By that time, the Volcker Rule had grown into a 953-page document, adding to the 2,400 page Dodd-Frank Act. In contrast, the Federal Reserve Act of 1913 which created the Federal Reserve System was only 31 pages long, and the Glass-Steagall Act of 1933, the most important regulatory legislation post the Great Depression, was only 37 pages.

Anticipating tighter regulation, big banks started to gradually retreat from businesses prohibited by the Rule well before details were finalized. In September 2010, two months after the passage of Dodd-Frank, JP Morgan first announced the closing of its proprietary trading desks[4]. Two days later, Goldman Sachs followed[5]. Several other banks such as Morgan Stanley, Bank of America, Citi Group, and RBC announced the shutdown of their proprietary trading desks one after another from January 2011 to April 2014, spanning the whole rulemaking period[6].

With banks retreating from proprietary trading due to the anticipation of tighter regulation, market participants started to worry about unintended consequences of the Volcker Rule on banks' market making capacity. Although the Volcker Rule exempts market-making related trading activities, critics argued that the proposed metrics of exemption would nevertheless substantially discourage the use of market making discretion (Duffie, 2012). Supporting this claim, there seemed to be evidence that banks started shedding their corporate bond inventories. Figure 2 shows one of the most cited stylized facts: the amount of corporate bonds held by dealer banks declined by nearly 80% since their peak of $235 billion in 2007 according to Federal Reserve data[7]. In terms of the percentage of the total corporate bond outstanding, the decline is from more than 5% in 2007 to less than 1% in 2014. Because the corporate bond market relies heavily on the banks to make market, this dramatic decline of dealer inventories has fed concerns about deteriorating market liquidity under Dodd-Frank and the Volcker Rule.

As the above discussion should have made clear, the protracted rulemaking process and complicated anticipatory response by market participants posit a daunting challenge for researchers trying to pin down when the regulations started to take effect on market liquidity, or if it had any effect at all. To address this challenge, we employ statistical methods which allow us to estimate the dates of breaks in liquidity without requiring a priori knowledge of the exact timing.

The Volcker Rule is by no means the only regulation that may affect market liquidity. Basel III and other post-crisis financial regulations could also constrain banks' market making ability. The implementation process of various regulations overlaps each other, adding another layer of complexity. In this study, we are mostly interested in the cumulative effect of post-crisis regulations. Nevertheless, the estimated timing of the breaks and the heterogeneous effects on different types of securities can shed some light on which regulation might be the most relevant.

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[4] See "J.P. Morgan to Close Proprietary-Trading Desks" by Matthias Rieker, The Wall Street Journal, Sep 1, 2010.

[5] See "Goldman shutting proprietary trading", The Globe and Mail, September 3, 2010.

[6] See "Morgan Stanley Team to Exit In Fallout From Volcker Rule" by Aaron Lucchetti, The Wall Street Journal, January 11, 2011; "Bank Of America Is Shutting Down Merrill's Bond Prop Trading Desk" by Katya Wachtel, Business Insider, June 10, 2011; "Citigroup to Close Prop Trading Desk" by Kevin Roose, The New York Times, January 27, 2012; "RBC to Close Proprietary-Trading Desk", by Rob Copeland, The Wall Street Journal, April 15, 2014.

[7] See "Markets: The Debt Penalty" by Tracy Alloway, Financial Times, September 10, 2013. See also "Investors Raise Alarm Over Liquidity Shortage" by Christopher Whittall and Juliet Samuel, The Wall Street Journal, March 18, 2015.

Corporate Bonds Liquidity Measures: Construction

1. Amihud measure. Amihud (2002) constructs an illiquidity measure based on the theoretical model of Kyle (1985). We use a slightly modified version of this measure following Dick-Nielsen, Feldhütter, and Lando (2012). The Amihud proxy measures the price impact of a trade per unit traded. For a given bond, define r_{j,i,t} as the return and Q_{j,i,t} as the trade size (in million $) of the j-th trade on day i in month t. The daily Amihud measure is the average of the absolute returns divided by the corresponding trade size within day i:

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \frac{|r_{j,i,t}|}{Q_{j,i,t}}$$

where $N_{i,t}$ is the number of trades recorded on day i. We exclude retail trades (i.e. trades below $100,000 in volume), as they are unlikely to have price impact. At least two trades are required on a given day to calculate the measure, and we define a monthly Amihud measure by taking the median of the daily measures within month t.

2. Imputed round-trip cost (IRC). Feldhütter (2011) shows that if a bond that does not trade for days suddenly has two or three trades with the same volume within a short period of time (one day in our definition), then such trades are likely part of a pre-matched arrangement in which a dealer has matched a buyer and a seller. These trades are defined as a set of imputed round-trip trades. The difference between highest and lowest price in a set of imputed round-trip trades is the bid-ask spread collected by the dealer, which is a measure of liquidity of the bond. We follow this approach. Specifically, for a given bond, on each day i we identify sets of imputed round-trip trades indexed by k. A set of imputed round-trip trades involves two or more transactions with the same trading volume. Define $P^{max}_{k,i,t}$ (resp. $P^{min}_{k,i,t}$) as the maximum (resp. minimum) price among all the transactions in the k-th set of round-trip trades for that bond on day i in month t. The imputed round-trip cost of k-th set of round-trip trade is defined as:

$$IRT_{k,i,t} = \frac{P^{max}_{k,i,t} - P^{min}_{k,i,t}}{P^{min}_{k,i,t}}$$

We define a monthly IRC measure by taking the mean of the IRC of each set of imputed round-trip trades within month t, weighted by the number of transactions involved in each set of imputed round-trip trades.

3. Roll measure. The intuition of the Roll measure is as follows: the transaction price tends to bounce between the bid and ask price, which causes consecutive trade returns to be negatively correlated. Under certain assumptions as shown in Roll (1984), the Roll measure equals to the bid-ask spread. The Roll measure is defined as two times the square root of the negative covariance between two consecutive daily returns $R_{i,t}$ and $R_{i-1,t}$ in month t. If the covariance is positive, the covariance is replaced with zero.

$$Roll_t = 2\left(-Cov\left(R_{i,t}, R_{i-1,t}\right)\right)^{\frac{1}{2}}$$

4. Non-block trades. A trade is defined as non-block trade if the trading volume is less than $5 million for investment-grade bonds, and $1 million for high-yield bonds. The frequency of non-

block trades is defined as the ratio between the number of non-block trades and the total number of trades in month t.

5. Size (negative log). Lower liquidity is usually associated with smaller size of trade. We first take the negative logarithm of the par value for each trade, then compute the monthly median for each security.

6. Turnover (negative). The annualized turnover for month t is defined as the annualized trading volume divided by the amount outstanding. In what follows we take the negative of turnover as proxy of illiquidity, for consistency with the other measures.

7. Zero trading days. We define this measure as the ratio between days with zero trade and the number of trading days in month t.

8 . Variability of Amihud and 9. Variability of IRC. Investors not only care about the current level of liquidity, but also the risk of future liquidity. Therefore, we create the standard deviations of the daily Amihud measure and imputed round-trip costs in a month as measures of liquidity risk.

Treasury Liquidity Measures: Construction

1. Yield curve fitting noise. Hu, Pan, and Wang (2013) proposes a market-wide liquidity measure by exploiting the connection between the amount of arbitrage capital in the market and observed "noise" in U.S. Treasury bonds---the shortage of arbitrage capital allows yields to deviate more freely from the curve, resulting in more noise in prices. They construct the noise measure by first fitting Treasury daily prices into a smooth yield curve, and then calculate the mean squared errors[8].

2. On-the-run premium. On-the-run Treasury bond (latest issue) usually enjoys a price premium over old bonds with similar maturity. We follow Gurkaynak et al. (2007) to construct the liquidity premium as the difference between the yield of this synthetic off-the-run bond and the on-the-run bond.

3. Roll measure and 4. Turnover (negative). Roll measure and Turnover (negative) measure are constructed similarly as in the case of corporate bonds.

[8] We obtain the measure from the authors' website at http://www.mit.edu/~junpan/Noise_Measure.xlsx

Breaks in Trends and a Simulation Example

In this section we first provide a simple example to illustrate the flexibility of the dynamic factor model to capture breaks in trends, which are a realistic type of structural break in our setting. Suppose the illiquidity measure, l_t is jointly driven by supply of liquidity, s_t, and demand for liquidity, d_t. Suppose that post-crisis regulations lead to a upward trend with a constant drift γ in illiquidity from τ+1:

$$l_t \ = -\alpha s_t + \beta d_t + e_t \ \ t = 1, \ldots, \tau$$

$$l_t \ = -\alpha s_t + \beta d_t + \gamma(\mathrm{t} - \tau) + + e_t \ \ t = \tau + 1, \ldots, T$$

Taking the first difference of the above equation system gives:

$$x_t \ = -\alpha f_{1t} + \beta f_{2t} + \epsilon_t \ \ t = 1, \ldots, \tau$$

$$x_t \ = -\alpha f_{1t} + \beta f_{2t} + \gamma f_{3t} + \epsilon_t \ \ t = \tau + 1, \ldots, T$$

Where $x_t \ = l_t - l_{t-1}$ is the innovation in illiquidity, $f_{1t} \ = s_t - s_{t-1}$ is the supply factor, $f_{2t} \ = d_t - d_{t-1}$ is the demand factor, $f_{3t} \ = 1$ is the regulation factor, and $\epsilon_t = e_t - e_{t-1}$ is the differenced measurement errors. It is immediately obvious that the break in trend can be reformulated as a break in the loading on the regulation factor, which can be consistently estimated by our methodology.

We simulate a panel of 180 liquidity measures to illustrate the power of our tests. To mimic our empirical application, we simulate 180 liquidity measures driven by two latent factors: a supply factor and a demand factor. The two factors follow AR(1) process with autocorrelation of 0.5, and cross-correlation of 0.5. The loading parameters on the two latent factors are drawn from N(0,1). A structural break occurs in July 2010 where 180 liquidity measures start to load on a new regulation factor, which follows AR(1) process with autocorrelation of 0.5 and an upward drift of 0.1. The loading parameters on the regulation factor follows N(0,0.2). The cross-correlation between regulation and supply and demand factor is also 0.5. A detailed discussion of simulation and the Monte Carlo evidence of power and size of the tests can be found in Chen, Dolado and Gonzalo (2014). online appendix Figure 2 plots the simulated liquidity index, defined as the average of 180 standardized simulated liquidity measures. The blue solid line is the path with the structural break, and the green dotted line plots the counterfactual scenario where regulation has no effects by design. The star sign indicates the date when the structural break happens. The difference between the two paths is the regulation-induced liquidity gap. We can see that the magnitude of liquidity deterioration is very small at the beginning compared with the normal fluctuations of liquidity, and builds up very slowly. We conduct our structural break tests described in Section 3.2 and 3.3. The estimated break date is marked by the vertical dashed line. Despite of the small magnitude, both tests successful identify the date of the structural break.

We also use the dynamic factor model to estimate the counterfactual path of liquidity assuming there is no structural break. We first use the observed data before the break to estimate the loadings. Specifically, we regress each of the 180 liquidity measures on the estimated factors. Then we predict the counterfactual path of liquidity assuming the factor loadings in the post-break period are the same as the pre-break period. The red dash line shows the estimated path. Our estimation accurately traces out the true counterfactual path. Such accuracy is obtained because the large cross-section dimension (N=180) of our liquidity measures compensate the relatively short time span for loading estimation (62 months).

Our second simulation example illustrates the flexibility of our methodology to detect multiple breaks. This is crucial since other policy interventions (e.g. unconventional monetary policy) also occurred in our sample period, which raises concerns on potential confounding effects. Assume in addition to the structural break induced by the regulation, set for the example's sake in July 2010 (Dodd-Frank signed into law), an unconventional monetary policy move generates a second structural break in September 2012 (the date of announcement of QE-Infinity – the largest open-ended unconventional purchases). The second structural break leads liquidity to improve, which may cancel the deterioration in liquidity. As shown in the online appendix Figure 3, the first break in July 2010 makes the simulated illiquidity index (green line) increases comparing to the counterfactual path (red line), while the second break in September 2012 makes the simulated illiquidity index (blue line) decreases comparing to the counterfactual path (green line). Despite the fact that the second break almost cancels out quantitatively the effect of the first break by the end of our sample, our estimation successfully identifies both structural breaks, as shown in the online appendix Table 4. The reason why we can identify both breaks is that, even if they move in opposite directions, they are not coincident. In summary, as long as additional structural breaks do not occur coincidentally to the breaks of interest to our analysis, our estimator will separately identify them.

Single Breakpoint Tests for the Dynamic Factor Model

We discuss here the application of Chen, Dolado and Gonzalo (2014) using the 2005-14 monthly sample and our full matrix X of N=180 differenced and standardized time series.

Online appendix Figure 8 reports the Sup-Wald and the Sup-LM test statistics of the full interval over which the unknown breakpoint is allowed to belong given a conservative π_0 =0.3. Such sample restriction is due to power loss concerns for the Sup tests (Andrews, 1993). Our interval of search of breakpoints covers the period between January 2008 and January 2012. Online appendix Figure 8 also reports the Andrews (1993) critical values above which the structural break is significant at the 10% and 5% confidence. We perform the analysis for any possible number of factors in the range estimated in online appendix Table 8.

As evident from online appendix Figure 8, the Sup tests systematically pick breaks in factor loadings (at 5% confidence) when we allow a number of estimated factors above 4. Typically the Sup statistic indicates the breakpoint as occurring during the 2008-2009 recession or shortly after. This is informative because again such dating does not correspond to regulatory events of prominence, but rather corresponds to the financial crisis itself. In essence what the Chen, Dolado and Gonzalo (2014) methodology allows us to exclude is that a structural break in the underlying factor structure of the disaggregate liquidity occurred around dates of post-crisis regulatory activity[9].

The methodology in this subsection has focused on a single breakpoint, a restriction that, given the multitude of potential shocks affecting the U.S. financial system during our period of analysis, one should find unwarranted. We relax this restriction in the paper.

[9] In online appendix Table 9, we report the number of factors before and after the break.

Simulation Example for Unconventional Monetary Policy

During the post-crisis regulatory intervention period, the Federal Reserve conducted two rounds of Quantitative Easing in late 2010 and late 2012. These dates fall into our regulatory intervention period and the coincidence of these two policies may prima facie raise concerns on potential confounding effects.

Conceptually, having additional structural breaks due to QE does not cause problems within our econometric setting and for estimation because our methodologies allow for multiple structural breaks even quite closely spaced in terms of timing. Below we will discuss Montecarlo simulations to support this statement.

Let us assume that in addition to the structural break induced by the regulation, set for the example's sake in July 2010 (Dodd-Frank signed into law), an unconventional monetary policy move generates a second structural break in September 2012 (the date of announcement of QE-Infinity – the largest open-ended unconventional purchase). The second structural break leads liquidity to improve, which may cancel the deterioration in liquidity due to regulation. As shown in the attached Figure 3, the first break in July 2010 makes the simulated illiquidity index (green line) increase comparing to the counterfactual path (red line), while the second break in September 2012 makes the simulated illiquidity index (blue line) decrease comparing to the counterfactual path (green line). Despite the fact that the second break almost cancels out quantitatively the effect of the first break by the end of our sample, our estimation successfully identifies both structural breaks, as shown in the attached Table 4. The reason why we can identify both breaks is that, even if they move in opposite directions, they are not precisely coincident. In summary, as long as additional structural breaks do not occur coincidentally to the breaks of interest to our analysis, our tests will separately identify them.

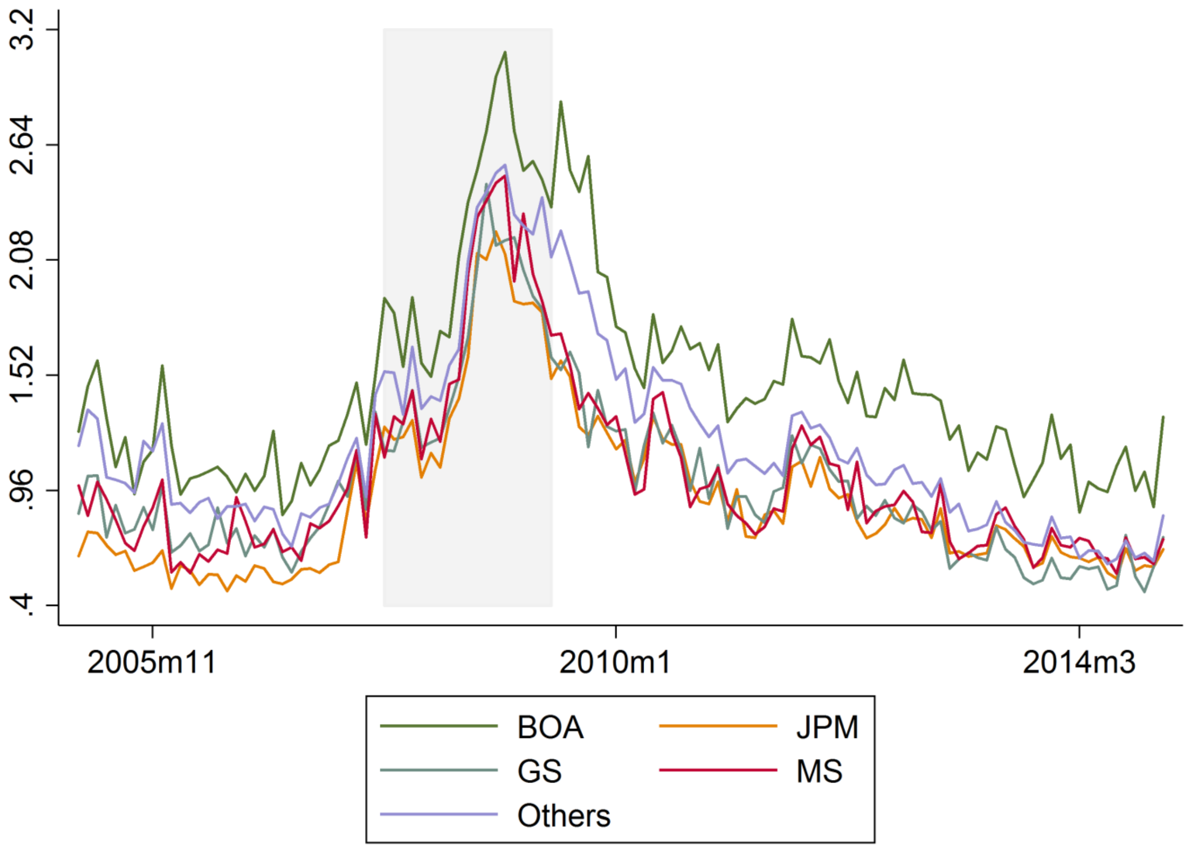

Figure 1. Time Series of Liquidity Measures (Underwriter-Level): Amihud

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

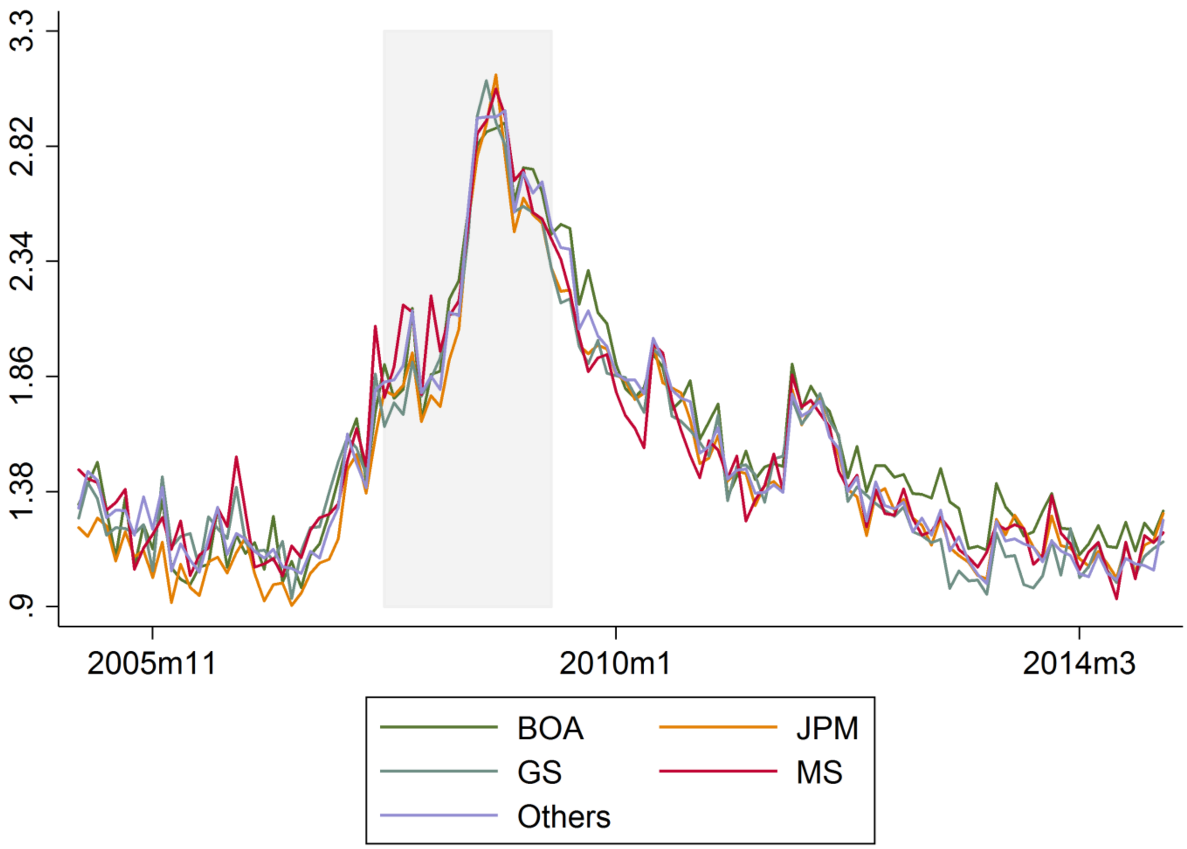

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Amihud (sd)

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

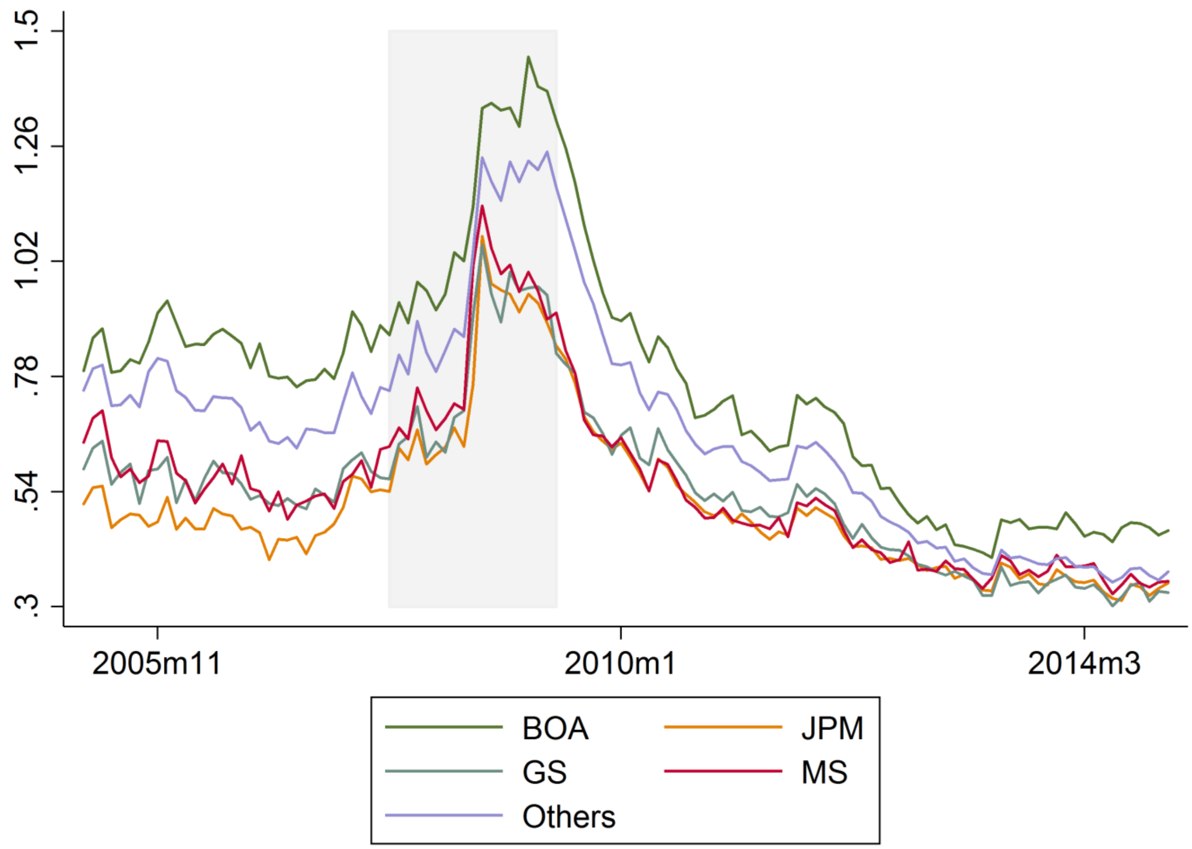

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): IRC

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

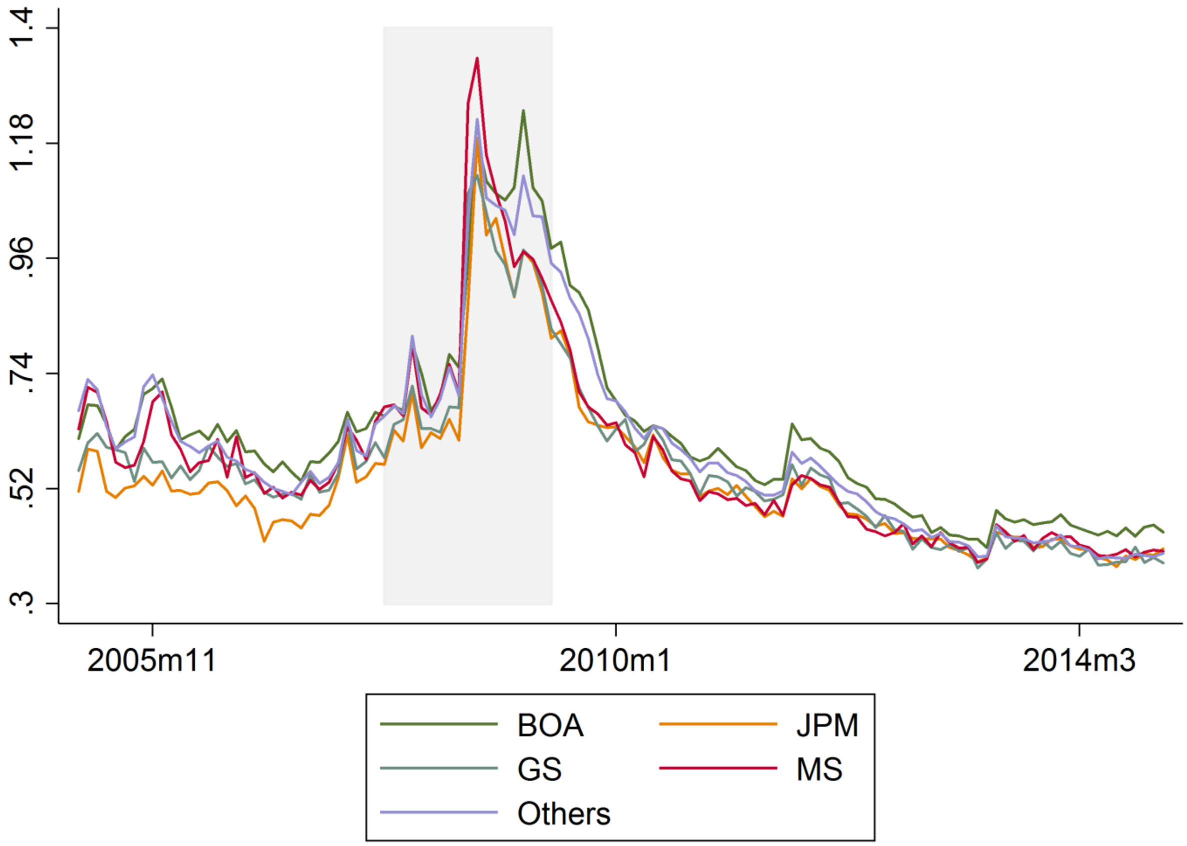

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): IRC (sd)

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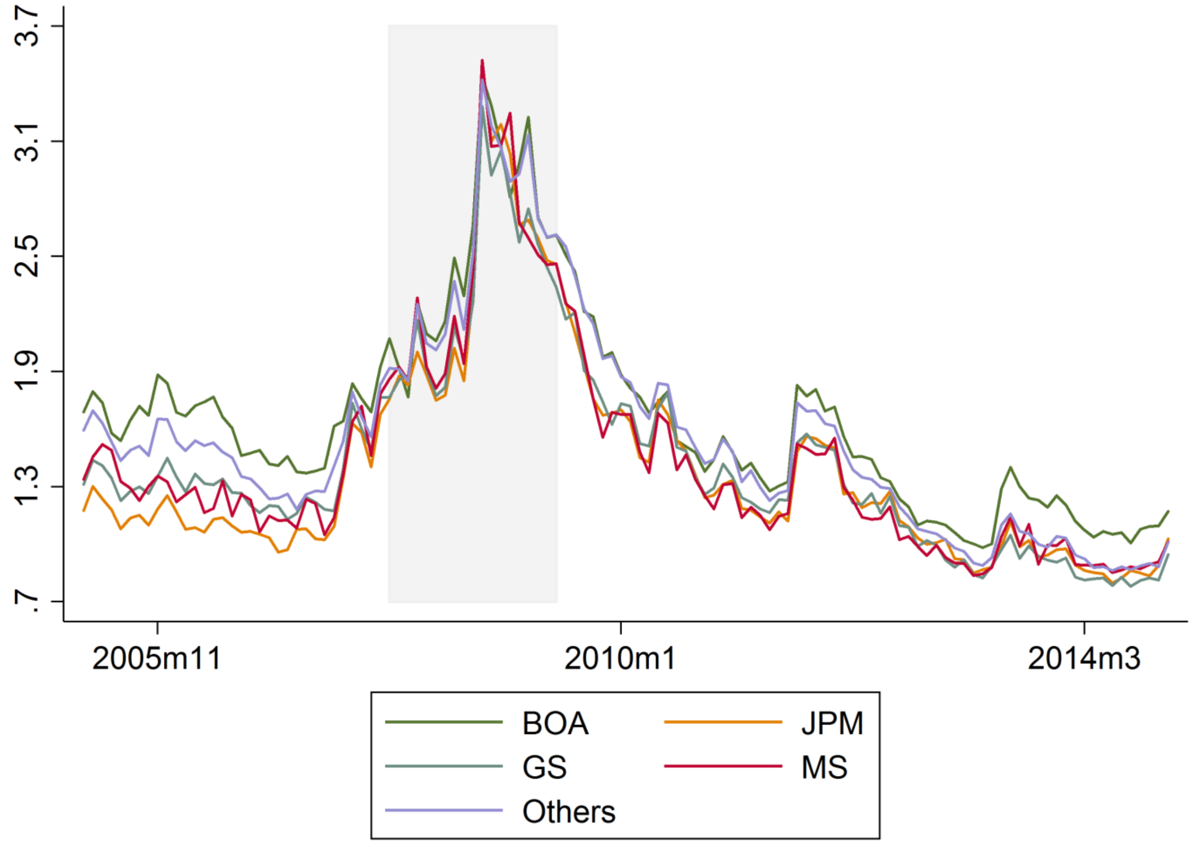

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Roll

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

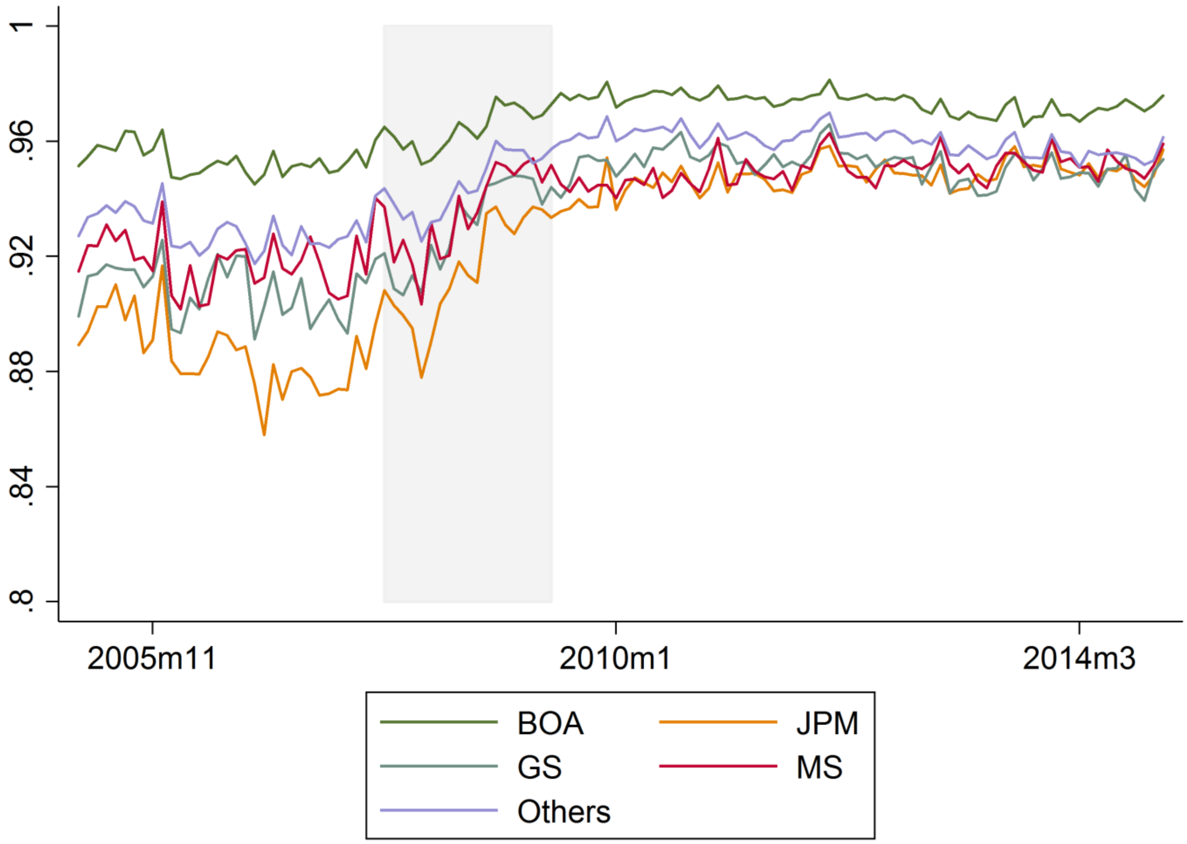

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Non-block Trade

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

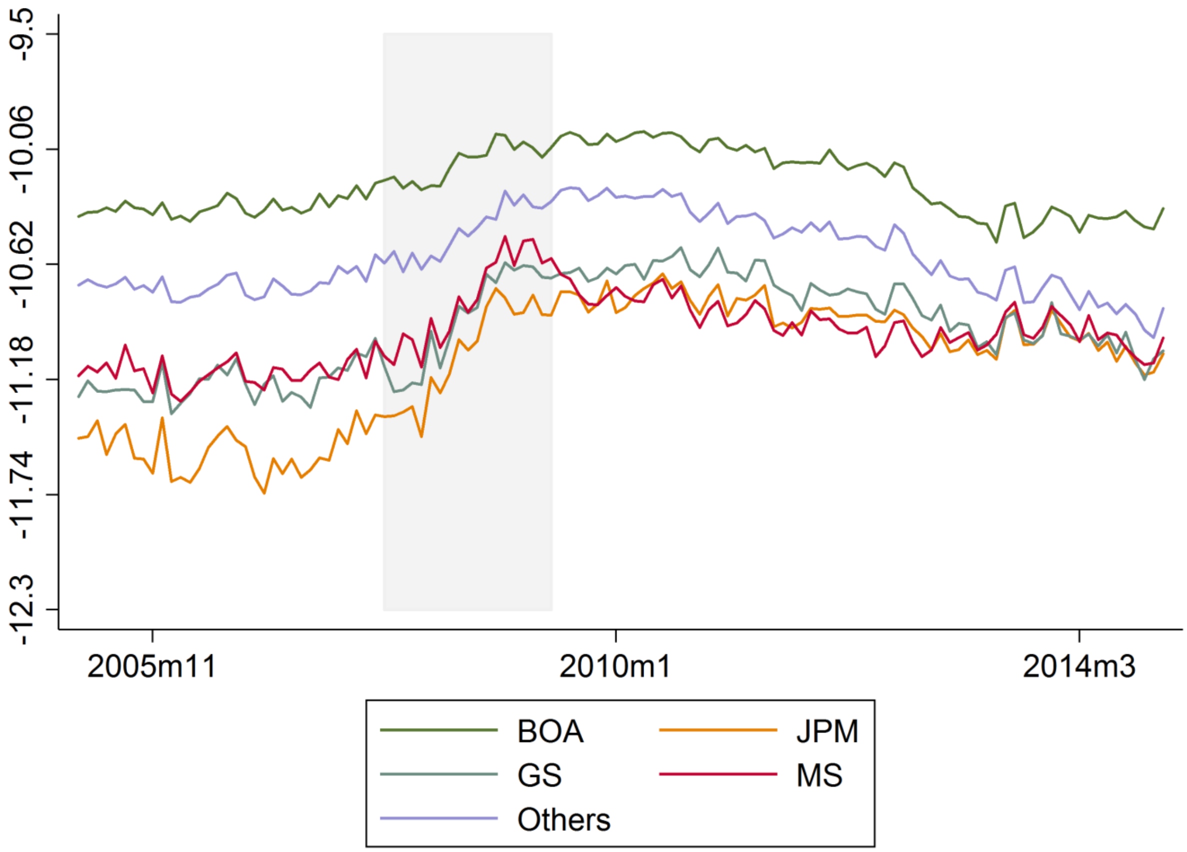

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Size (negative)

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

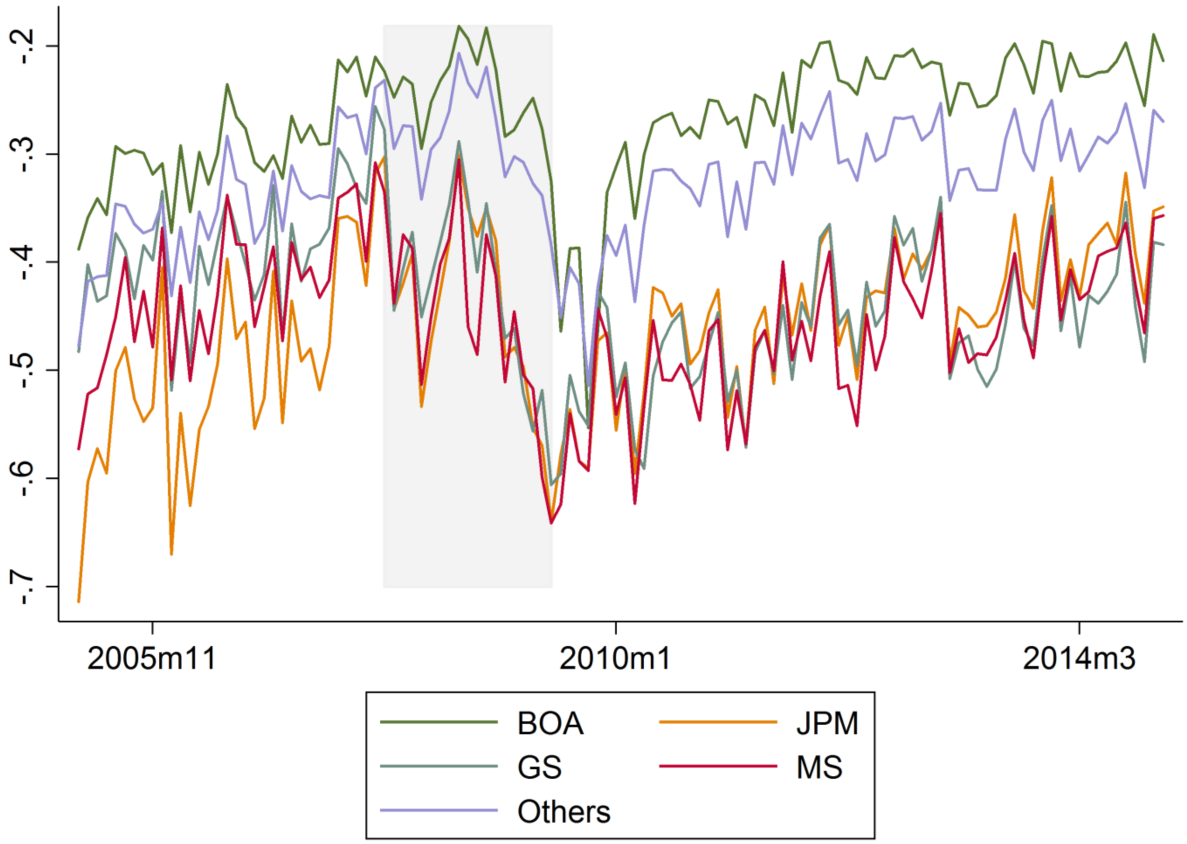

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Turnover (negative)

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

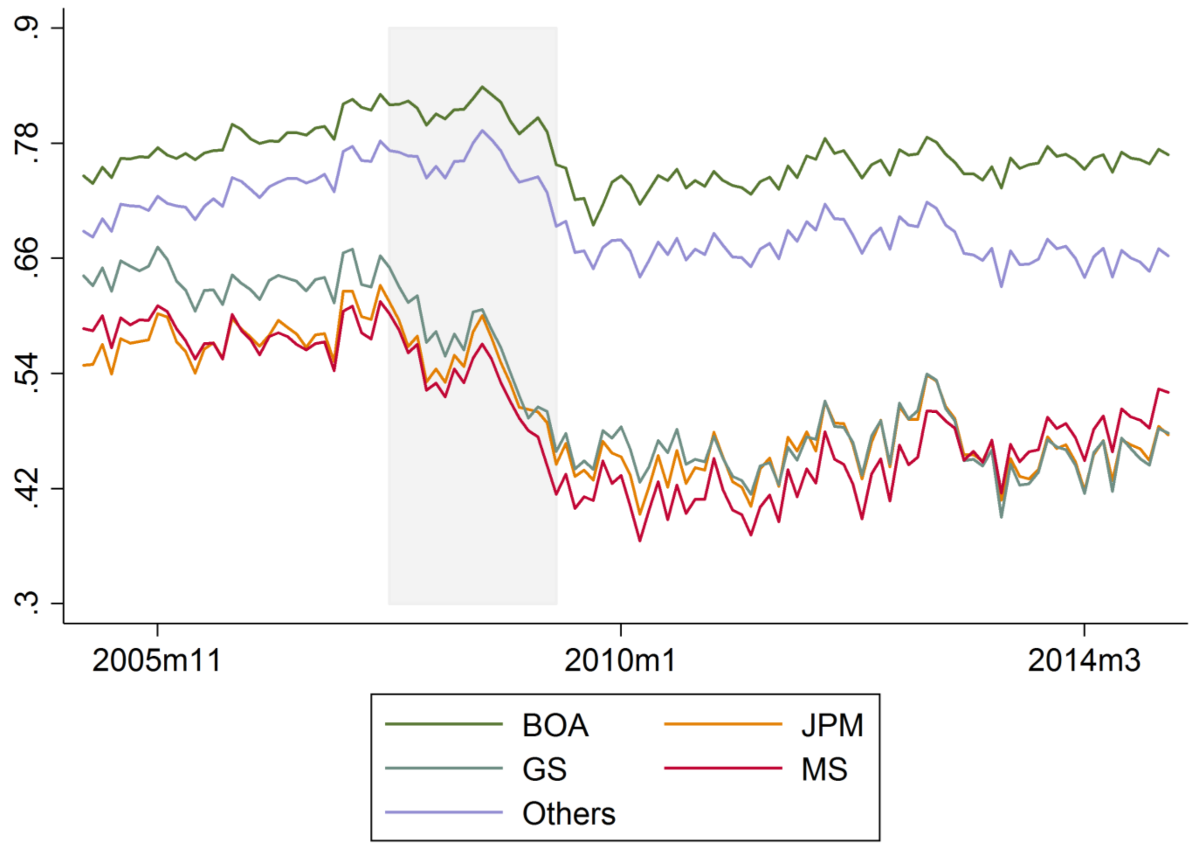

Figure 1 (continued). Time Series of Liquidity Measures (Underwriter-Level): Zero-trading Days

Notes: This graph shows the time series of liquidity measures of U.S. corporate bonds underwritten by four big banks and all the other underwriters combined. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

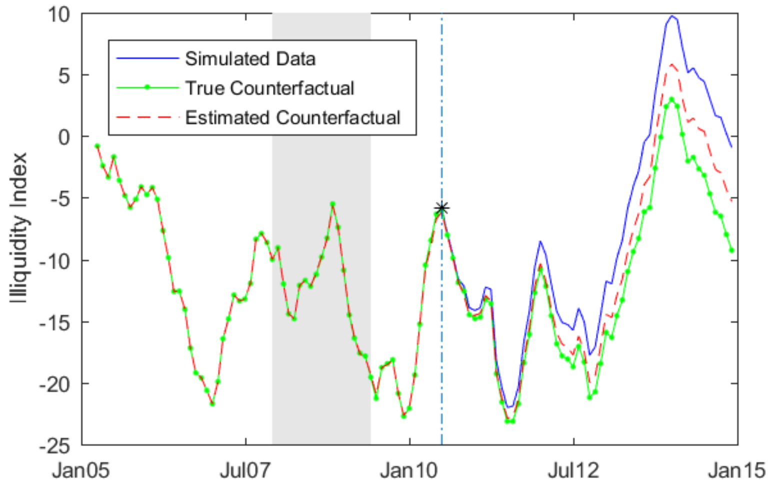

Figure 2. Simulated Illiquidity Index

Notes: This graph shows the average of 180 simulated liquidity measures over time. The blue solid line represents the average of 180 liquidity measures if regulation leads to a gradual deterioration in market liquidity, while the green dotted line represents counterfactual scenario where regulation has no effects. The dashed vertical line indicates the date of true and estimated structural break in the latent factor structure. The red dashed line is the estimated counterfactual path. The break date is estimated by Chen, Dolado, and Gonzalo (2014) and Bai and Perron (2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

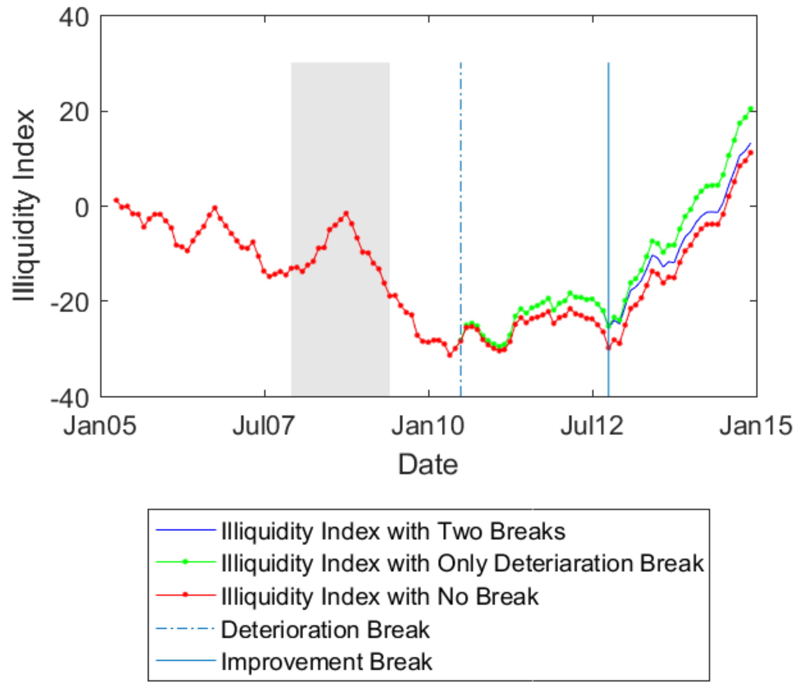

Figure 3. Simulated Illiquidity Index

Notes: This graph shows the average of 180 simulated liquidity measures over time. The blue /green/ red solid line represents the average of 180 liquidity measures with two/one/zero structural breaks. The dashed vertical line indicates the date of the first structural break which leads to deterioration in liquidity, and the solid line indicates the date of the second structural break which leads to improvement in liquidity. The break date is estimated by Chen, Dolado, and Gonzalo (2014) and Bai and Perron (2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

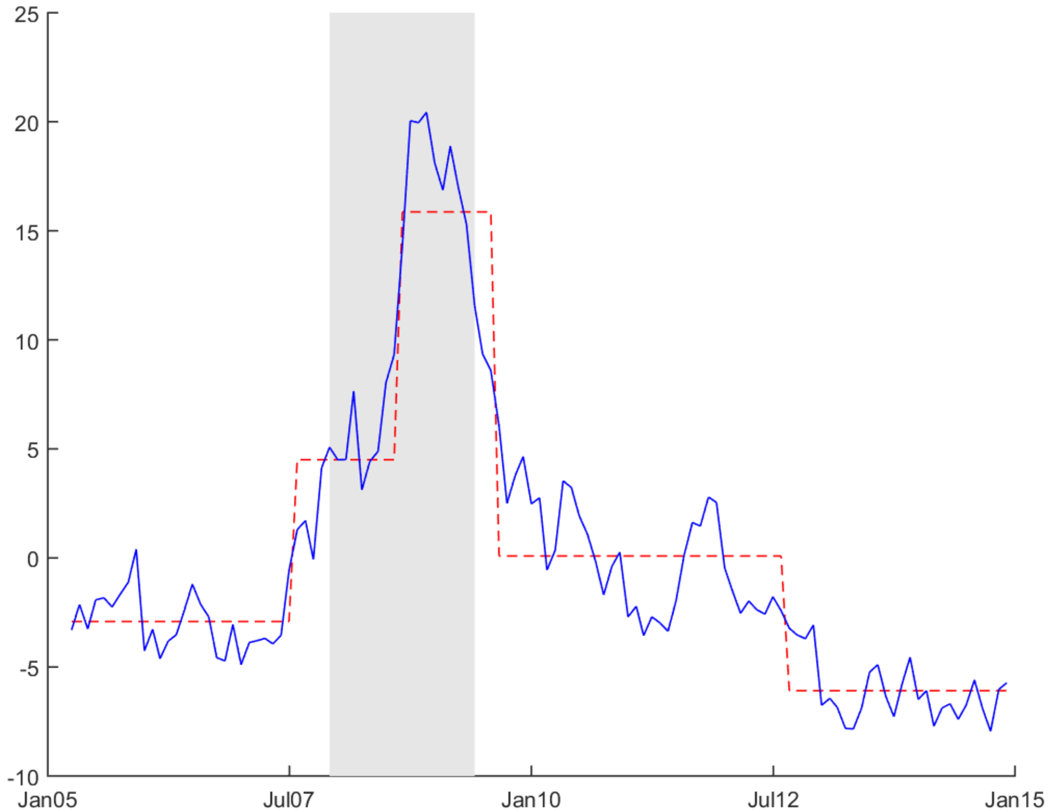

Figure 4. Time Series of Aggregate Liquidity Index of U.S. Corporate Bonds

Notes: This graph shows the time series of aggregate liquidity index of U.S. corporate bond market (blue line), and the estimated mean for each sub-period (red dashed line). The break dates (dates with a shift in the level of the red dashed line) are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

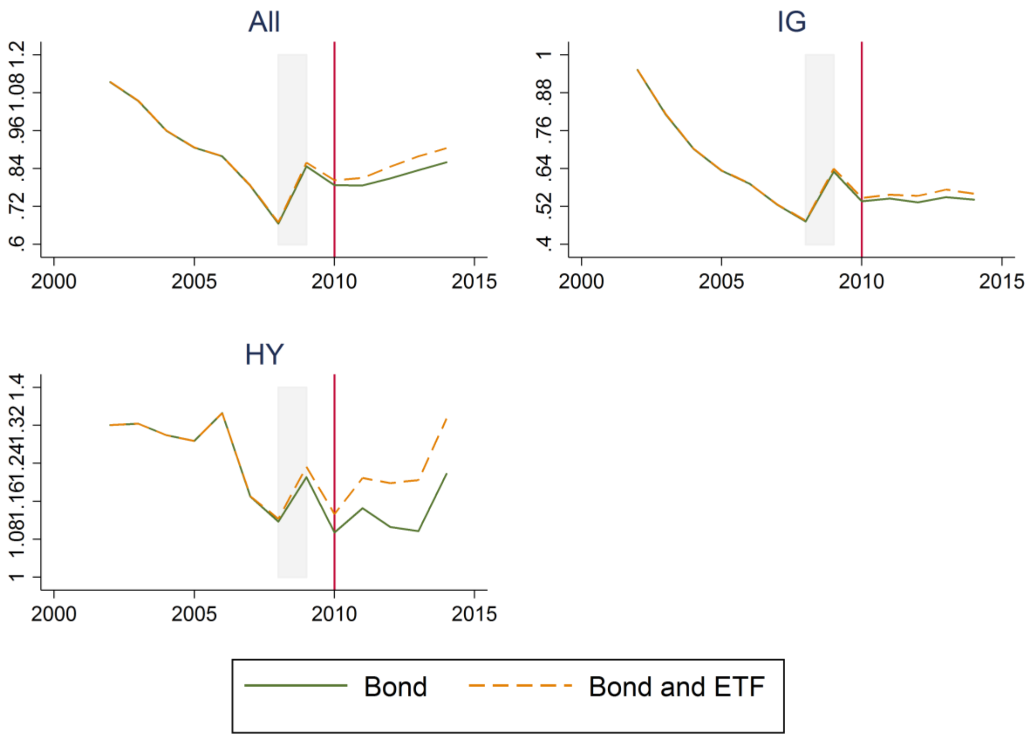

Figure 5. Corporate Bond Turnover from 2002 to 2014

Notes: This graph shows the aggregate bond turnover from 2002 to 2014. The solid line is the raw turnover, and the dashed line is the turnover adjusted by including corporate bond ETFs. The vertical line indicates the passage of Dodd-Frank Act (July, 2010). The corporate bond data is from SIFMA and the ETF data is from Bloomberg.

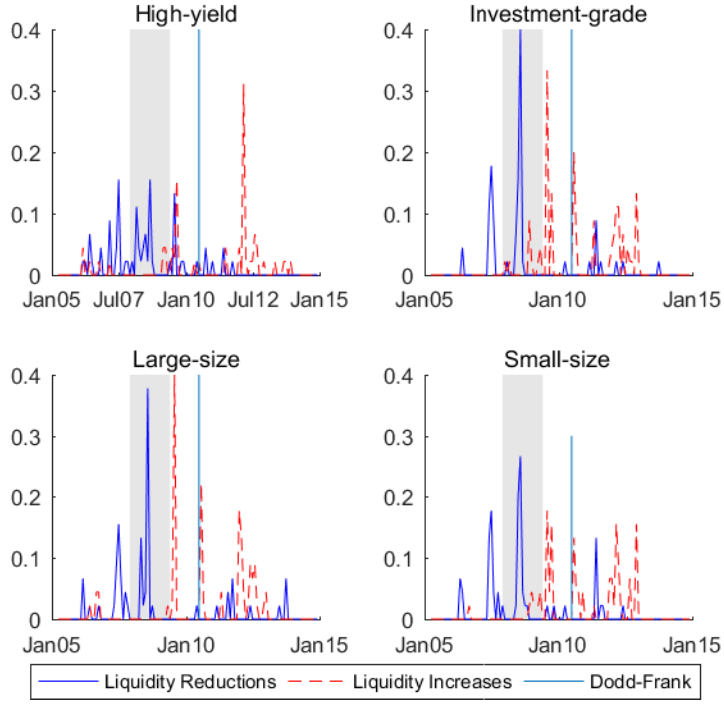

Figure 6. Breaks in the Means of Liquidity by Bond Type (Disaggregate-level)

Notes: This graph shows the decomposition of break dates by bond type. The x-axis shows the dates and the y-axis shows the corresponding fraction of the 45 (=9×5) liquidity measures of each bond type which have a break at this date. The break dates are estimated using the Bai and Perron (1998-2003) approach with 5 percent significance level. The solid vertical line indicates the passage of Dodd-Frank Act (July, 2010). The sample period is from April 2005 to December 2014. The data frequency is monthly.

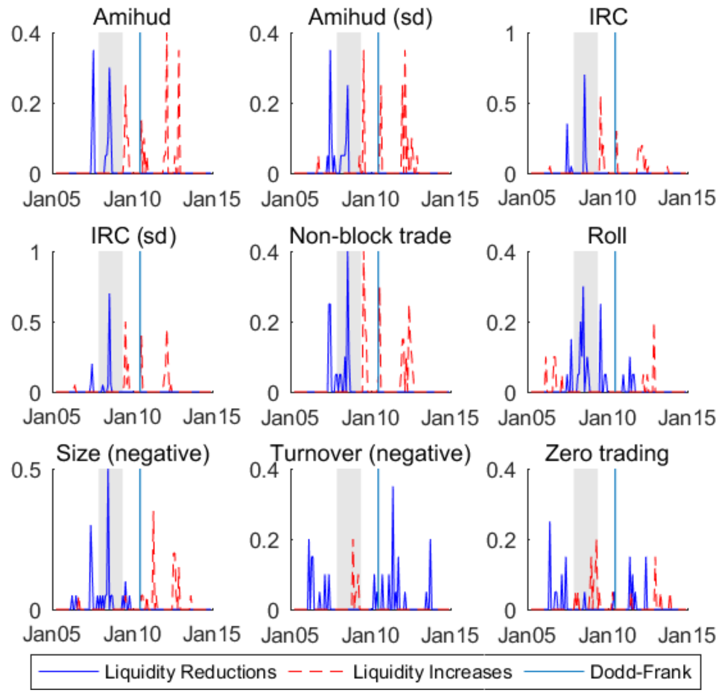

Figure 7. Breaks in the Means of Liquidity by Measure (Disaggregate-level)

Notes: This graph shows the decomposition of break dates by liquidity measure. The x-axis shows the dates and the y-axis shows the corresponding fraction of the 20 (=5×2×2) series of each liquidity measure which have a break at this date. The break dates are estimated using the Bai and Perron (1998-2003) approach with 5 percent significance level. The solid vertical line indicates the passage of Dodd-Frank Act (July, 2010). The sample period is from April 2005 to December 2014. The data frequency is monthly.

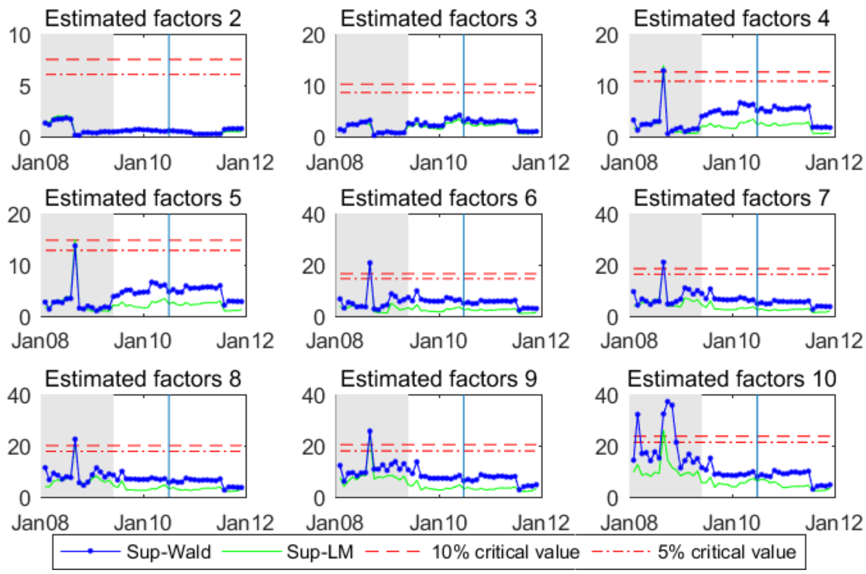

Figure 8. Test Statistics of a Single Break in the Dynamic Factor Structure

Notes: This graph shows the test statistics of a single break in factor structure of 180 disaggregate-level liquidity measures employing the Chen, Dolado, and Gonzalo (2014) approach. The sample period is from April 2005 to December 2014. The solid vertical line indicates the passage of Dodd-Frank Act (July, 2010). The data frequency is monthly. The grey area indicates recession.

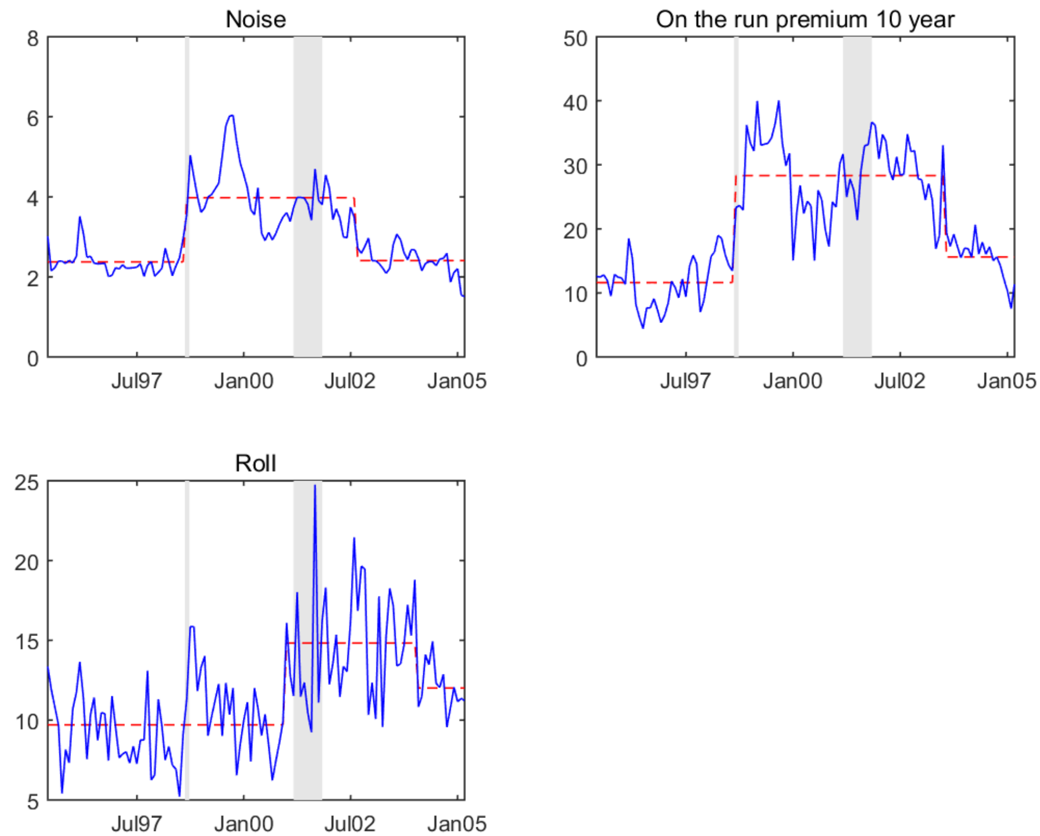

Figure 9. Time Series of Liquidity of the U.S. Treasury Bonds (June 1995 to March 2005)

Notes: This graph shows the time series of liquidity measures of U.S. Treasury market (blue line), and the estimated mean for each sub-period (red dashed line). The break dates (dates with a shift in the level of the red dashed line) are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from June 1995 to March 2005. The data frequency is monthly. The first grey area indicates LTCM crisis, and the second grey area indicates the recession in 2001.

Table 1: Summary Statistics of the U.S. Corporate Bond Liquidity (Aggregate-level)

Measures	N	mean	sd	p10	p25	p50	p75	p90
Amihud	117	1.29	0.48	0.79	0.94	1.17	1.47	2.12
Amihud (sd)	117	1.57	0.48	1.10	1.19	1.43	1.83	2.35
IRC	117	0.70	0.24	0.40	0.49	0.70	0.82	1.08
IRC (sd)	117	0.61	0.18	0.42	0.47	0.58	0.67	0.88
Roll	117	1.59	0.54	0.96	1.23	1.52	1.81	2.41
Non-block trade	117	0.96	0.01	0.93	0.94	0.96	0.97	0.97
Size (negative)	117	-10.48	0.20	-10.71	-10.66	-10.51	-10.28	-10.18
Turnover (negative)	117	-0.29	0.05	-0.36	-0.32	-0.28	-0.25	-0.23
Zero-trading	117	0.74	0.03	0.71	0.72	0.74	0.76	0.79

Notes: This table shows the summary statistics of 9 aggregate-level liquidity measures for the U.S. corporate bond market. The sample period is from April 2005 to December 2014. The data frequency is monthly. The unit of Amihud, Amihud (sd), IRC, IRC (sd), and Roll is percentage point. The unit of Non-block trade, Turnover (negative) and Zero-trading is 1.

Table 2: Correlation Table of the U.S. Corporate Bond Liquidity (Aggregate Level)

	Amihud	Amihud (sd)	IRC	IRC (sd)	Roll	Non-block trade	Size (negative)	Turnover (negative)
Amihud (sd)	0.98							
IRC	0.88	0.84						
IRC (sd)	0.91	0.88	0.98					
Roll	0.93	0.93	0.96	0.97				
Non-block trade	0.29	0.33	-0.15	-0.06	0.01			
Size (negative)	0.75	0.76	0.51	0.51	0.58	0.65		
Turnover (negative)	-0.07	0.05	-0.28	-0.20	-0.10	0.27	0.00	
Zero-trading	0.40	0.43	0.54	0.52	0.56	-0.43	0.03	0.37

Notes: This table shows the correlations among 9 aggregate-level liquidity measures for the U.S. corporate bond market. The sample period is from April 2005 to December 2014. The data frequency is monthly.

Table 3. Sample Mean and Standard Deviation of Liquidity (Disaggregate-level)

Bank	Bond Type	Amihud	Amihud (sd)	IRC	IRC (sd)	Roll	Non-block trade	Size (negative)	Turnover (negative)	Zero-trading
B	High-yield	0.71	1.21	0.48	0.52	1.33	0.70	-11.87	-0.36	0.63
		(0.26)	(0.32)	(0.15)	(0.16)	(0.4)	(0.09)	(0.52)	(0.12)	(0.05)
B	Investment-grade	1.58	1.63	0.79	0.63	1.68	0.98	-10.14	-0.26	0.78
		(0.53)	(0.51)	(0.26)	(0.18)	(0.54)	(0.01)	(0.15)	(0.06)	(0.03)
B	Large-size	0.88	1.52	0.57	0.65	1.28	0.93	-10.98	-0.65	0.18
		(0.49)	(0.55)	(0.24)	(0.25)	(0.59)	(0.02)	(0.2)	(0.17)	(0.04)
B	Small-size	1.58	1.60	0.78	0.63	1.68	0.97	-10.18	-0.25	0.79
		(0.51)	(0.48)	(0.26)	(0.18)	(0.52)	(0.01)	(0.15)	(0.06)	(0.03)
GS	High-yield	0.83	1.32	0.55	0.58	1.51	0.74	-11.55	-0.32	0.66
		(0.33)	(0.46)	(0.17)	(0.17)	(0.51)	(0.07)	(0.47)	(0.08)	(0.07)
GS	Investment-grade	1.02	1.54	0.55	0.56	1.42	0.96	-10.86	-0.45	0.51
		(0.43)	(0.5)	(0.17)	(0.16)	(0.53)	(0.02)	(0.21)	(0.08)	(0.09)
GS	Large-size	0.86	1.54	0.59	0.67	1.26	0.94	-10.74	-0.75	0.15
		(0.58)	(0.56)	(0.27)	(0.28)	(0.59)	(0.02)	(0.24)	(0.16)	(0.05)
GS	Small-size	1.02	1.52	0.54	0.55	1.46	0.94	-10.94	-0.39	0.57
		(0.39)	(0.47)	(0.15)	(0.14)	(0.51)	(0.02)	(0.24)	(0.06)	(0.08)

Notes: This table shows the sample mean and standard deviation (in brackets) of 180 underwriter-level liquidity measures for the U.S. corporate bond market. The list of underwriters includes Bank of America (B), Goldman Sachs (GS), JP Morgan (JPM), Morgan Stanley (MS), and all the other underwriters (OT). The sample period is from April 2005 to December 2014. The data frequency is monthly. The unit of Amihud, Amihud (sd), IRC, IRC (sd), and Roll is percentage point. The unit of Non-block trade, Turnover (negative) and Zero-trading is 1.

Bank	Bond Type	Amihud	Amihud (sd)	IRC	IRC (sd)	Roll	Non-block trade	Size (negative)	Turnover (negative)	Zero-trading
JPM	High-yield	0.78	1.34	0.53	0.56	1.41	0.70	-11.79	-0.39	0.61
		(0.29)	(0.4)	(0.15)	(0.16)	(0.42)	(0.1)	(0.61)	(0.09)	(0.05)
JPM	Investment-grade	0.94	1.51	0.51	0.54	1.39	0.95	-11.01	-0.47	0.49
		(0.42)	(0.51)	(0.17)	(0.16)	(0.57)	(0.02)	(0.29)	(0.08)	(0.07)
JPM	Large-size	0.72	1.38	0.51	0.61	1.20	0.93	-10.89	-0.69	0.16
		(0.49)	(0.5)	(0.22)	(0.22)	(0.57)	(0.02)	(0.23)	(0.14)	(0.04)
JPM	Small-size	0.96	1.51	0.52	0.54	1.42	0.93	-11.11	-0.43	0.54
		(0.39)	(0.48)	(0.16)	(0.15)	(0.55)	(0.03)	(0.32)	(0.08)	(0.06)
MS	High-yield	0.94	1.51	0.58	0.62	1.58	0.75	-11.47	-0.37	0.63
		(0.34)	(0.38)	(0.17)	(0.19)	(0.49)	(0.06)	(0.35)	(0.09)	(0.05)
MS	Investment-grade	1.03	1.55	0.55	0.58	1.42	0.96	-10.90	-0.46	0.48
		(0.46)	(0.51)	(0.18)	(0.19)	(0.56)	(0.01)	(0.17)	(0.08)	(0.08)
MS	Large-size	0.86	1.43	0.55	0.63	1.18	0.94	-10.96	-0.72	0.16
		(0.55)	(0.53)	(0.25)	(0.27)	(0.57)	(0.02)	(0.19)	(0.17)	(0.04)
MS	Small-size	1.06	1.58	0.56	0.57	1.48	0.94	-10.95	-0.41	0.55
		(0.42)	(0.48)	(0.16)	(0.16)	(0.55)	(0.02)	(0.18)	(0.06)	(0.07)
OT	High-yield	0.77	1.32	0.53	0.56	1.43	0.72	-11.70	-0.36	0.66
		(0.24)	(0.3)	(0.14)	(0.14)	(0.41)	(0.08)	(0.49)	(0.11)	(0.04)
OT	Investment-grade	1.26	1.57	0.69	0.61	1.58	0.97	-10.48	-0.32	0.71
		(0.51)	(0.54)	(0.24)	(0.19)	(0.58)	(0.01)	(0.19)	(0.05)	(0.04)
OT	Large-size	0.73	1.37	0.51	0.61	1.18	0.93	-10.97	-0.65	0.18
		(0.46)	(0.51)	(0.23)	(0.24)	(0.56)	(0.02)	(0.16)	(0.14)	(0.05)
OT	Small-size	1.27	1.58	0.69	0.60	1.60	0.95	-10.54	-0.30	0.73
		(0.48)	(0.5)	(0.23)	(0.18)	(0.56)	(0.02)	(0.2)	(0.05)	(0.03)

Table 4. Break Dates in the Levels of Liquidity (Simulated Example with Two Breaks)

	Break Dates				
2	07-Jun				
3	10-Jun				
4	10-Jun	12-Oct			
5	10-Jun	12-Oct			
6	10-Jun	12-Oct			
7	10-Jun	12-Oct	13-Nov		
8	10-Jun	12-Oct	13-Nov		
9	10-Feb	11-Feb	12-Oct	13-Dec	
10	06-May	10-Feb	11-Feb	12-Oct	13-Dec

Notes: This table shows the break dates in factor structure of a simulated sample of liquidity measures employing the Chen, Dolado, and Gonzalo (2014) and Bai and Perron (1998-2003) approach with 5 percent significance level. One structural break occurs in July 2010, which leads to liquidity deterioration, while the other structural break occurs in September 2012, which leads to liquidity improvement. We estimate the top 10 principal components from the differenced and standardized liquidity measures, then run the tests iteratively assuming that there are k principal factors, where k = 2 to 10.

Table 5. Break Dates in the Levels of Liquidity (Aggregate-level)

Measure	Break Dates			
Amihud	Aug07	Aug08	Dec09	Dec12
Amihud (sd)	Mar12			
IRC	Aug08	Oct09	Mar12	
IRC (sd)	Aug08	Oct09	Mar12	
Roll	Feb08	Oct09	Jun12	
Non-block trade	Oct07	Oct08	Dec12	
Size (negative)	Jun07	Jul08	May11	Oct12
Turnover (negative)	Jan07			
Zero trading	Jun06	Jun07	May09	

Notes: This table lists break dates in the levels of 9 aggregate-level liquidity measures of the U.S. corporate bond market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

Table 6. Double Maximum Test Statistics of Breaks in the Levels of Liquidity (Aggregate-level)

Measures	WDmax	5% critical value of WDmax	UDmax	5% critical value of UDmax
Amihud	75.81	10.39	44.74	9.52
Amihud (sd)	62.02	10.39	36.60	9.52
IRC	278.58	10.39	184.60	9.52
IRC (sd)	97.20	10.39	58.38	9.52
Roll	55.66	10.39	32.84	9.52
Non-block trade	231.80	10.39	152.66	9.52
Size (negative)	214.44	10.39	126.54	9.52
Turnover (negative)	76.27	10.39	45.01	9.52
Zero trading	86.06	10.39	50.78	9.52

Notes: This table lists the Dmax statistics of break dates in the levels of 9 aggregate-level liquidity measures of the U.S. corporate bond market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The null hypothesis is that there is no break, and the alternative hypothesis is that there is at least one break. The data frequency is monthly. The critical values are obtained from Bai and Perron (1998) with 10% of trimming rates.

Table 7: Sequential Test Statistics of Multiple Breaks in the Means of Liquidity (Aggregate-level)

Measure	F(2|1)	5% critical value of F(2|1)	F(3|2)	5% critical value of F(3|2)	F(4|3)	5% critical value of F(4|3)	F(5|4)	5% critical value of F(5|4)
Amihud	14.63	10.55	35.57	11.36	20.61	12.35	10.76	12.97
Amihud (sd)	3.46	10.55						
IRC	23.01	10.55	16.25	11.36	5.86	12.35		
IRC (sd)	20.89	10.55	25.83	11.36	3.00	12.35		
Roll	18.29	10.55	24.25	11.36	5.97	12.35		
Non-block trade	11.63	10.55	29.91	11.36	5.07	12.35		
Spread	29.82	10.55	109.60	11.36	49.79	12.35	11.29	12.97
Turnover (negative)	3.18	10.55						
Zero trading	22.35	10.55	38.24	11.36	6.00	12.35		

Notes: This table lists the sequential test statistics of break dates in the levels of 9 aggregate-level liquidity measures of the U.S. corporate bond market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The critical values are obtained from Bai and Perron (1998) with 10% of trimming rates.

Table 8. Number of Dynamic Factors (Disaggregate-level)

Method	Number of Estimated Factors
Ahn & Horenstein (2013) ER	3
Ahn & Horenstein (2013) GR	3
Bai & Ng (2002) IC1	10
Bai & Ng (2002) IC2	8
Bai & Ng (2002) IC3	10
Bai & Ng (2002) PC1	10
Bai & Ng (2002) PC2	9
Bai & Ng (2002) PC3	10
Bai & Ng (2002) AIC3	10
Bai & Ng (2002) BIC3	4

Notes: This graph shows the estimated number of factors in 180 underwriter-level liquidity measures for the U.S. corporate bond market. The sample period is from April 2005 to December 2014. The liquidity measures are differenced and standardized. The data frequency is monthly. The maximum number of possible breaks is 10.

Table 9. Number of Factors Before and After Break: Single Break Test

Notes: This graph shows the estimated number of factors before and after the break dates in a panel of underwriter-level liquidity measures for the U.S. corporate bond market. The break dates are estimated using the sup-Wald test from Chen et al. (2014), and the numbers of factors before and after break are estimated using the eigenvalue ratio estimator from Ahn and Horenstein (2013). The sample period is from April 2005 to December 2014. The liquidity measures are differenced and standardized. The data frequency is monthly.

	# of Factors		
Whole Sample	Before Break	After Break	Break Dates
2	1	1	Jul08
3	2	2	Jun10
4	2	1	Sep08
5	2	1	Sep08
6	2	1	Sep08
7	2	1	Sep08
8	2	1	Sep08
9	2	1	Sep08
10	2	3	Oct08

Table 10: Break Dates of Liquidity Factor Structure (Disaggregate-level)

	Break Dates				
2	Aug08	Sep09			
3	Aug08	Sep09			
4	Aug08	Sep09			
5	Sep08	Dec09			
6	Aug06	Sep07	Sep08	Nov09	Aug11
7	May06	Sep07	Sep08	Nov09	Sep11
8	Aug06	Sep07	Sep08	Sep09	Sep10
9	Aug06	Sep07	Sep08	Mar10	Mar11
10	May06	Sep07	Sep08	Jul10	Sep11

Notes: This table shows the break dates in factor structure of the U.S. corporate bond market liquidity employing the Chen, Dolado, and Gonzalo (2014) and Bai and Perron (1998-2003) approach with 5 percent significance level. Liquidity measures are in underwriter-level. The sample period is from April 2005 to December 2014. We estimate the top 10 principal components from the differenced and standardized liquidity measures, then run the tests iteratively assuming that there are k principal factors, where k = 2 to 10.

Table 11: Double Maximum Test Statistics of Breaks in the Liquidity Factor Structure (Disaggregate-level)

Number of factors	WDmax	5% critical value of WDmax	UDmax	5% critical value of UDmax
2	22.51	10.39	19.59	9.52
3	51.15	13.66	44.17	12.59
4	400.32	16.07	314.23	14.85
5	172.29	18.38	125.93	17.00
6	546.64	20.30	399.88	18.91
7	1325.34	22.55	935.27	21.01
8	7.12E+13	24.34	5.08E+13	22.80
9	2.98E+04	26.10	2.45E+04	24.56
10	1.37E+14	27.99	1.00E+14	26.48

Notes: This table shows the double maximum test statistics of break in factor structure of the U.S. corporate bond market liquidity employing the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. We estimate the top 10 principal components from the differenced and standardized liquidity measures, then run the tests iteratively assuming that there are k principal factors, where k = 2 to 10. The null hypothesis is that there is no break, and the alternative hypothesis is that there is at least one break. The critical values are obtained from Bai and Perron (1998) with 10% of trimming rates.

Table 12: Sequential Test Statistics of Multiple Breaks in the Liquidity Factor Structure (Disaggregate-level)

Number of factors	F(2|1)	5% critical value of F(2|1)	F(3|2)	5% critical value of F(3|2)	F(4|3)	5% critical value of F(4|3)	F(5|4)	5% critical value of F(5|4)
2	21.26	10.55	1.35	11.36				
3	32.37	13.83	7.36	14.73				
4	43.43	16.53	15.20	17.43				
5	22.11	18.56	7.38	19.53				
6	39.27	20.57	40.46	21.60	59.75	22.55	59.75	23.00
7	69.01	23.01	102.09	24.14	102.09	24.77	92.12	25.48
8	91.88	24.64	435.28	25.57	435.28	26.54	83.63	27.04
9	3752.16	26.42	1554.46	27.66	1554.46	28.25	36.52	28.99
10	1350.01	28.23	4688.40	29.44	12381.97	30.31	12381.97	30.77

Notes: This table shows the sequential test statistics of break in factor structure of the U.S. corporate bond market liquidity employing the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. We estimate the top 10 principal components from the differenced and standardized liquidity measures, then run the tests iteratively assuming that there are k principal factors, where k = 2 to 10. The critical values are obtained from Bai and Perron (1998) with 10% of trimming rates.

Table 13: Number of Factors of Each Subperiod: Multiple Break Test

Whole sample	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 4	Subperiod 5	Subperiod 6
2	1	1	3			
3	1	1	3			
4	1	1	3			
5	2	1	3			
6	1	3	2	1	3	2
7	1	3	2	1	2	2
8	1	3	2	1	3	2
9	1	3	2	1	1	2
10	1	3	2	1	2	2

Notes: This graph shows the estimated number of factors of each subperiod in a panel of underwriter-level liquidity measures for the U.S. corporate bond market. The break dates are estimated using Bai and Perron (1998-2003) approach with 5 percent significance level, and the number of factors of each subperiod is estimated using the eigenvalue ratio estimator from Ahn and Horenstein (2013). The sample period is from April 2005 to December 2014. The liquidity measures are differenced and standardized. The data frequency is monthly.

Table 14: Liquidity Principal Components and Determinants

	(1) Factor 1	(2) Factor 2	(3) Factor 3	(4) Factor 4	(5) Factor 5
VIX	0.0413***	-0.0136	0.0148	0.0120	0.0247**
	[0.0124]	[0.0124]	[0.0102]	[0.0131]	[0.0106]
BBB	0.00669	-0.00282	0.0274	0.0104	0.0385*
	[0.0155]	[0.0165]	[0.0211]	[0.0150]	[0.0198]
FFR	-0.0108	0.00787	0.0224**	-0.00425	0.0146
	[0.00905]	[0.00998]	[0.0111]	[0.0136]	[0.0110]
Term	-0.00268	-0.0158	0.0463***	0.000163	-0.00361
	[0.0128]	[0.0128]	[0.0149]	[0.00934]	[0.0107]
Breakeven	-0.00246	0.0183	-0.00784	-0.000244	0.0301*
	[0.0145]	[0.0146]	[0.0210]	[0.0159]	[0.0164]
QE	-0.0140	0.0136	-0.0565***	-0.00634	0.0114
	[0.0103]	[0.00935]	[0.0169]	[0.0112]	[0.0155]
TED	0.0231	0.0104	-0.00973	-0.0379***	-0.00689
	[0.0195]	[0.00999]	[0.0205]	[0.0102]	[0.0142]
Bond Fund	0.00458***	-0.00874***	-0.00703***	0.00203*	-0.00596***
	[0.000973]	[0.00122]	[0.000963]	[0.00104]	[0.00113]
inventory	0.0119	0.00871	0.00241	-0.00464	0.0113
	[0.00716]	[0.00829]	[0.00639]	[0.00837]	[0.00696]
Observations	117	117	117	117	117
Adjusted R-squared	0.369	0.019	0.207	0.071	0.152

Notes: This table shows multivariate regression of principal components of 180 liquidity measures on potential determinants that affect liquidity.

Table 14 (continued): Liquidity Principal Components and Determinants

	(6) Factor 6	(7) Factor 7	(8) Factor 8	(9) Factor 9	(10) Factor 10
VIX	-0.0239**	-0.0131	-0.0191	-0.0129	0.00293
	[0.0119]	[0.0145]	[0.0177]	[0.0164]	[0.0114]
BBB	-0.00272	-0.00905	0.0212	0.0116	0.0144
	[0.0161]	[0.0251]	[0.0207]	[0.0205]	[0.0198]
FFR	0.0150	-0.00218	-0.00127	0.0141	0.0147
	[0.0111]	[0.0136]	[0.0122]	[0.0141]	[0.0121]
Term	0.0113	0.00329	-0.0120	0.0314*	0.000697
	[0.0120]	[0.0134]	[0.0161]	[0.0163]	[0.0117]
Breakeven	0.0124	-0.00728	-0.0312**	-0.00667	0.0193
	[0.0158]	[0.0133]	[0.0149]	[0.0133]	[0.0169]
QE	0.0210	0.000757	-0.0268**	0.0217*	0.0111
	[0.0132]	[0.0114]	[0.0117]	[0.0125]	[0.0134]
TED	0.0134	0.0422***	0.00195	-0.0166	0.0152
	[0.0185]	[0.0124]	[0.00964]	[0.0142]	[0.0104]
Bond Fund	-0.00481***	-0.00178	-0.00189	-0.00470***	0.00130
	[0.00115]	[0.00123]	[0.00129]	[0.00125]	[0.000943]
inventory	-0.0122	-0.00921	0.000989	-0.00457	-0.0104
	[0.0130]	[0.00810]	[0.00806]	[0.00882]	[0.00820]
Observations	117	117	117	117	117
Adjusted R-squared	0.042	0.090	0.133	0.063	-0.001

Notes: This table shows multivariate regression of principal components of 180 liquidity measures on potential determinants that affect liquidity.

Table 15. Summary Statistics of the U.S. Treasury Liquidity

Measure	N	mean	sd	p10	p25	p50	p75	p90
Noise	117	3.14	3.24	1.20	1.48	1.93	3.33	6.51
On the run premium	117	13.48	12.62	3.33	6.23	8.94	16.39	28.73
Roll	117	13.37	4.09	8.62	10.35	12.73	15.83	19.23
Turnover	117	-11.48	3.93	-17.64	-14.76	-9.79	-8.11	-7.39

Notes: This table shows the summary statistics of liquidity measures for the U.S. Treasury market. The sample period is from April 2005 to December 2014. The data frequency is monthly. The unit of Noise, On the run premium and Roll measure is basis point. The unit of Turnover (negative) is 1.

Table 16. Correlation Table of the U.S. Treasury Liquidity

	Noise	On the run premium	Roll
On the run premium	0.90		
Roll	0.62	0.72	
Turnover	0.03	-0.08	-0.37

Notes: This table shows the correlations between liquidity measures for the U.S. Treasury market. The sample period is from April 2005 to December 2014. The data frequency is monthly.

Table 17: Break Dates of the U.S. Treasury Liquidity

Measure		Break Dates		
Noise	Jun07	Jun08	Jun09	
On the run premium 10 year	Jan11			
Roll	Aug07	Jun09	Nov11	
Turnover (negative)	Mar06	Oct08	Apr10	Nov11

Notes: This table lists break dates in the levels of liquidity measures of U.S. Treasury market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

Table 18: Double Maximum Test Statistics of Multiple Breaks in the Means of the U.S. Treasury Liquidity

Measure	WDmax	5 percent critical value of WDmax	UDmax	5 percent critical value of UDmax
Noise	12.10	10.39	7.14	9.52
On the run premium	54.14	10.39	35.88	9.52
Roll	119.05	10.39	87.48	9.52
Turnover (negative)	276.59	10.39	276.59	9.52

Notes: This table lists the double maximum statistics of break dates in the levels of liquidity measures of U.S. Treasury market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5 percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The null hypothesis is that there is no break, and the alternative hypothesis is that there is at least one break. The critical values are obtained from Bai and Perron (1998).

Table 19: Sequential Test Statistics of Multiple Breaks in the Means of the U.S. Treasury Liquidity

Measure	F(2|1)	5% critical value of F(2|1)	F(3|2)	5% critical value of F(3|2)	F(4|3)	5% critical value of F(4|3)	F(5|4)	5% critical value of F(5|4)
Noise	10.56	10.55	21.63	11.36	9.65	12.35		
On the run premium 10 year	5.65	10.55						
Roll	25.12	10.55	31.19	11.36	1.26	12.35		
Turnover (negative)	34.26	10.55	16.50	11.36	16.50	12.35	12.23	12.97

Notes: This table lists the double maximum statistics of break dates in the levels of liquidity measures of U.S. Treasury market. The dates are estimated by the Bai and Perron (1998-2003) approach with 5percent significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The critical values are obtained from Bai and Perron (1998).

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