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ABSTRACT

The aftermath of the 2008-09 U.S. financial crisis has been characterized by regulatory intervention of unprecedented scale. Although the necessity of a realignment of incentives and constraints of financial markets participants became a shared posterior after the near collapse of the U.S. financial system, considerable doubts have been subsequently raised on the welfare consequences of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 and its various subcomponents, such as the Volcker Rule. The possibility of permanently inhibiting the market making capacity of large banks, with dire consequences in terms of under-provision of market liquidity, has been repeatedly raised. This paper presents systematic evidence from four different estimation strategies of the absence of breakpoints in market liquidity for fixed-income asset classes and across multiple liquidity measures, with special attention given to the corporate bond market. The analysis is performed without imposing restrictions on the exact dating of breaks (i.e. allowing for anticipatory response or lagging reactions to regulation) and focusing both on levels and dynamic latent factors. We report both single breakpoint and multiple breakpoint tests and analyze the liquidity of corporate bonds matched to their main underwriters making markets on those assets. Post-crisis U.S. regulatory intervention does not appear to have produced structural deteriorations in market liquidity.

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1 Introduction

The aftermath of the 2008-09 financial crisis has witnessed one of the most active periods of regulatory intervention in U.S. financial history since the New Deal (Barr, 2012). A centerpiece of this sweeping reaction to the near collapse of the financial system, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank), was signed into law in July 2010. With Dodd-Frank, hundreds of regulatory rulemaking requirements have been subsequently met, affecting virtually every dimension of modern financial activity, from derivatives trading to housing finance to capital requirements for depository institutions. In the backdrop of this intervention, a lack of rigorous assessment of the complex costs and benefits of the new rules has been highlighted (Cochrane, 2014).

Pertinently to this debate, this paper investigates the claim that U.S. post-crisis financial regulatory overreach might have adversely affected the provision of market liquidity in a vast class of financial assets, structurally decreasing liquidity levels and increasing liquidity risk in fixed-income markets.

Such claim is linked, although not uniquely, to a specific set of provisions embedded within recent legislation, the so-called Volcker Rule, statutorily delineated in Section 619 Title VI of the 2010 Dodd-Frank Act and finalized by multiple regulatory agencies in January 2014. According to this provision, any banking entity is prohibited from engaging in proprietary trading or from acquiring or retaining an ownership interest in, sponsoring or having certain relationships with a hedge fund or private equity fund, subject to certain exemptions. Although this is in no way the only dimension of Dodd-Frank along which serious welfare losses or liquidity shortages could have been potentially triggered, it emerged as one of the most hotly debated, with roughly 17,000 public comments filed during the process of regulatory rulemaking (Bertrand, Bombardini and Trebbi, 2015). Specifically, some commentators[1] have highlighted how by placing undue artificial limits on securities inventory

[1] For instance regulators write in the final version of the Volcker Rule (p.5578 Federal Register / Vol. 79, No. 21 / Friday, January 31, 2014 / Rules and Regulations) "*As discussed above, several commenters stated that the proposed rule would impact a banking entity's ability to engage in market making related activity. Many of these commenters represented that, as a result, the proposed exemption would likely result in reduced liquidity[...]*" and the Federal Register explicitly mentions on the matter of reduced liquidity comments received from "*AllianceBernstein; Rep. Bachus et al. (Dec. 2011); EMTA; NASP; Wellington; Japanese Bankers Ass'n.; Sen. Hagan; Prof. Duffie; Investure; Standish Mellon; IR&M; MetLife; Lord Abbett; Commissioner Barnier; Quebec; IIF; Sumitomo Trust; Liberty Global; NYSE Euronext; CIEBA; EFAMA; SIFMA et al. (Prop. Trading) (Feb. 2012); Credit Suisse (Seidel); JPMC; Morgan Stanley; Barclays; Goldman (Prop. Trading); BoA; Citigroup (Feb. 2012); STANY; ICE; BlackRock; SIFMA (Asset Mgmt.) (Feb. 2012); BDA (Feb. 2012); Putnam; Fixed Income Forum/Credit Roundtable; Western Asset Mgmt.; ACLI (Feb. 2012); IAA; CME Group; Wells Fargo (Prop. Trading); Abbott Labs et al. (Feb.14, 2012); Abbott Labs et al. (Feb. 21, 2012); T. Rowe Price; Australian Bankers Ass'n. (Feb. 2012); FEI; AFMA; Sen. Carper et al.; PUC Texas; ERCOT; IHS; Columbia Mgmt.; SSgA (Feb. 2012); PNC et al.; Eaton Vance; Fidelity; ICI (Feb. 2012); British Bankers' Ass'n.; Comm. on Capital Markets Regulation;*

and retained risk and directly affecting inter-dealer trading, the Volcker Rule could have severely limited market liquidity[2]. When recently the Congressional debate shifted on the merits of regulatory relief, one of the provisions considered for rolling back within Dodd-Frank included the prohibition of proprietary trading on the part of insured banking entities and their affiliates below certain thresholds[3].

A balanced view of the potential adverse welfare consequences of such provision is summarized in Duffie (2012): "*The Agencies' proposed implementation of the Volcker Rule would reduce the quality and capacity of market making services that banks provide to U.S. investors. Investors and issues of securities would find it more costly to borrow, raise capital, invest, hedge risks, and obtain liquidity for their existing positions. Eventually, non-bank providers of market-marking services would fill some or all of the lost market making capacity, but with an unpredictable and potentially adverse impact on the safety and soundness of the financial system. These near-term and long-run impacts should be considered carefully in the Agencies' cost-benefit analysis of their final proposed rule. Regulatory capital and liquidity requirements for market making are a more cost effective method of treating the associated systemic risks.*" Duffie (2012) further remarks on the needs for an appropriate assessment of the cost and benefits of the rule, an assessment that the empirical analysis we perform systematically complements. Thakor (2012) raises similar issues.

This paper formally assesses the effect of the U.S. post-crisis regulatory intervention, encompassing the Dodd-Frank Act and its corollary parts as the Volcker Rule, on market liquidity of the U.S. fixed-income market. The biggest empirical challenge that we face is the complicated anticipatory response or lagging reaction during five years of protracted rulemaking process. To address this challenge, we employ a statistical method which allows

Union Asset; Sen. Casey; Oliver Wyman (Dec. 2011); Oliver Wyman (Feb. 2012) (providing estimated impacts on asset valuation, borrowing costs, and transaction costs in the corporate bond market based on hypothetical liquidity reduction scenarios); Thakor Study. The Agencies respond to comments regarding the potential market impact of the rule in Part IV.A.3.b.3., infra."

Available at http://www.gpo.gov/fdsys/pkg/FR-2014-01-31/pdf/2013-31511.pdf

[2]For example, on May 20, 2015 The Wall Street Journal in an article titled "Why Liquidity-Starved Markets Fear the Worst" reports "[..] *a large part of the explanation lies in changes to regulation aimed at addressing weaknesses exposed by the financial crisis. Banks must now hold vastly more capital, particularly against their trading books. The ring-fencing of proprietary trading in the U.S. and retail banking in the U.K. has also squeezed liquidity.* " Similar reasoning is implied by Alan Greenspan on the Financial Times on August 17, 2015, who writes "*Lawmakers and regulators, given elevated capital buffers, need to be far less concerned about the quality of the banks' loan and securities portfolios since any losses would be absorbed by shareholders, not taxpayers. This would enable the Dodd-Frank Act on financial regulation of 2010 to be shelved, ending its potential to distort the markets — a potential seen in the recent decline in market liquidity and flexibility.*"

[3]See S.1484 - Financial Regulatory Improvement Act of 2015, Title I: Regulatory Relief and Protection of Consumer Access To Credit. The bill is sponsored by Senate - Banking, Housing, and Urban Affairs Chairman Richard Shelby (R-AL).

us to estimate the dates of breaks in liquidity without requiring a priori knowledge of the exact timing. We provide systematic evidence of a lack of structural breaks in both liquidity levels and latent covariance and autocorrelation structure for a large set of liquidity proxies in fixed-income markets over the period associated to the post-crisis regulatory intervention. We also present concordant evidence from microeconometric approaches based on difference-in-differences of matched bonds samples that support these findings. Our work both qualifies frequent informal discussion on the lack of evidence of large deterioration in market liquidity provision (Dudley, 2015) and is relevant to the rigorous assessment of the welfare consequences of the Dodd-Frank Act in terms of hindering the market making capacity of large financial institutions, one of the main welfare costs observers have ascribed to the recent regulatory surge.

This paper employs four different estimation strategies. We first produce a large set of aggregate liquidity measures for the U.S. fixed-income markets and employ standard multiple breakpoint testing (Bai and Perron, 1998, 2003) on the liquidity level and liquidity risk time series. We explore the market for U.S. corporate bonds, an heterogenous asset class directly affected by the Volcker Rule. We also study U.S. Treasuries, an asset class not covered by the Volcker Rule directly, but one in which recent episodes of trading disruption have been observed (e.g. the flash crash of October 15, 2014). Several commentators have ascribed these phenomena to liquidity depletion.

For corporate bonds, we then disaggregate liquidity measures by classifying bonds by lead underwriter's identity. Given that original underwriters typically tend to make markets on the specific securities underwritten, this allows us to potentially identify bank-specific liquidity breaks and more nuanced disaggregated dynamics, as we further differentiate by issue size and credit rating. To this large panel of disaggregated liquidity measures we apply recent econometric approaches based on large factor models (Stock and Watson, 2011), appropriate to capture breaks in latent factor structures in the data. Specifically, our second methodology focuses on single breakpoint testing for large dynamic factor models (Chen et al., 2014). Our third methodology extends to more realistic multiple breakpoint testing for large dynamic factor models, transposing the intuition of Chen et al. (2014) to Bai and Perron (2003) type tests. Such methodologies robustly capture breaks in latent liquidity dynamics at the start and at the end of the 2008-09 crisis (and indeed can be employed to precisely time the beginning and end of the liquidity crisis). This reassures us on the tests having sufficient power within this specific empirical application. However, we detect no systematic statistical evidence of deterioration in liquidity provision due to overreaching regulation in the data from 2009 to the end of 2014.

As opposed to time series approaches delineated above, our fourth estimation strategy relies on a standard microeconometric approach in estimating liquidity deterioration around the finalization of the Volcker Rule, namely difference-in-differences matching (Heckman, Ichimura, Todd, 1997; Heckman, Ichimura, Smith, and Todd, 1998; Smith and Todd, 2005). In this part of the analysis we construct a dataset of bonds matched by issue size and credit rating, split between treatment and control based on whether the original underwriter is covered or not by Volcker Rule provisions. Matching allows for balancing between covered and non-covered bonds, assuaging concerns of attenuation due to heterogeneity across the two groups of securities.

Consistently across all four estimation strategies, this paper reports a lack of any form of systematic evidence of deterioration in liquidity levels or breaks in liquidity risk for corporate bonds. Moreover, during periods of heightened regulatory interventions, with big banks closing their proprietary trading desks and shedding bond inventories, market liquidity continued to improve. This is in stark contrast to the popular claim that the post-crisis regulatory intervention adversely affected market liquidity. To the best of our knowledge, this is one of the very first studies to statistically assess liquidity depletion related to regulatory activity post-2008.

Our work is related to several strands of literature in both economics and finance. The first strand of literature studies how balance sheets of financial intermediaries affect market liquidity. Early theoretical works by Garman (1976), Amihud and Mendelson (1980) and Ho and Stoll (1981) show that decrease in dealer inventories can lead to lower liquidity levels. Recent theoretical work by Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) further shows that limited market maker capital can explain why market liquidity varies over time. Many empirical works have since confirmed the main theoretical predictions of these models. Comerton-Forde et al. (2010) show that NYSE specialist inventory positions and trading revenues explain time variation in liquidity. Aragon and Strahan (2012) find that stocks held by Lehman-connected hedge funds experienced greater declines in market liquidity following the bankruptcy than other unconnected stocks. Dick-Nielsen et al. (2012) show how corporate bonds underwritten by Lehman Brothers and Bear Stearns experienced strain in liquidity during the subprime crisis. As validation, in this paper we also discuss in some detail the ability of our approach in picking up structural breaks for corporate bonds underwritten by Lehman Brothers and Bear Stearns.

A second strand of connected literature studies how liquidity affects asset prices. The idea that investors demand a liquidity premium for illiquid securities originates with Amihud and Mendelson (1986). Amihud, Mendelson, and Pedersen (2005) provide a comprehensive survey on how liquidity influences asset prices. Corporate bond liquidity has received extensive attention because of the so-called "credit spread puzzle" (i.e. spreads on corporate bonds tend to be many times wider than what is implied by expected default losses alone, see Amato and Remolona, 2003). Longstaff, Mithal, and Neis (2005) suggest that illiquidity may be a possible explanation for this puzzle. Later research has focused on measuring bond-specific liquidity. Edwards, Harris, and Piwowar (2007) estimate the effective bid–ask spread of corporate bonds, and find that transaction costs decrease significantly with trade size. Bao, Pan and Wang (2011) construct a closely related measure based on the theoretical model of Roll (1984). They find that illiquidity in corporate bonds is significantly greater than what can be explained by quoted bid–ask spreads. Feldhutter (2011) estimates imputed round-trip trades cost as the spread charged by a dealer in a dealer-intermediated trade. Dick-Nielsen et al, (2012) define a new liquidity measure as the first principal component of eight commonly used liquidity measures. They use this measure to study the corporate bond liquidity in the subprime crisis. Our dynamic factor model is somewhat related to this approach. For the Treasury market, Krishnamurthy (2002) studies the on-the-run premium and shows that variation in this premium is driven by the Treasury supply as well as aggregate factors affecting investors' preference for liquid assets. Hu, Pan and Wang (2012) proposes a liquidity measure for Treasury market as the observed "noise" in U.S. Treasury bonds in fitting a yield curve. They show that their noise measure captures episodes of liquidity crises of different origin.

A third and important strand of literature pertains to the cost-benefit analysis of financial regulation. By every stretch of imagination, this literature remains considerably underdeveloped relative to the potential welfare benefits of rigorous and data-driven regulatory intervention. Such limitations have been lamented not only by financial economists such as Cochrane (2014), but have been central motivation of judicial intervention[4]. Cochrane (2014) discusses at length the complexity of deriving meaningful assessments of regulatory counterfactuals in financial and banking regulation, question also discussed in Posner and Weyl (2013, 2014). Relative to the pessimistic assessment in Coates and John (2014) of the infeasibility of meaningful cost-benefit analysis in financial and banking regulation[5], our paper offers a more optimistic counterpoint, at least in terms of ex-post quantitative assessment[6] along the specific dimension of market liquidity depletion.

[4]Coates and John (2014) referring to Business Roundtable et al. v. SEC, 647 F. 3d 1144 (D.C. Cir. 2011), report that "*One panel of the U.S. Court of Appeals for the District of Columbia Circuit, composed entirely of Republican-appointed judges, has held that existing law requires the SEC to quantify the costs and benefits of its proposed rules*".

[5]Specifically speaking about the Volcker Rule, Coates and John (2014, p.73): "*Could the agencies go beyond conceptual CBA and conduct a reliable, precise, quantified CBA/FR? The short answer is no. There is simply no historical data on which anyone could base a reliable estimate of the benefits of preventing banks from engaging in proprietary trading or investing in hedge and private equity funds.*"

[6]See also Cochrane (2014)'s discussion of retrospective analysis of financial regulation.

A fourth literature touched by this paper revolves around the post-financial crisis policy responses. McCarthy, Poole, and Rosenthal (2013) debate political distortions in post-crisis responses, an issue also explored in Frieden (2015) and Mian, Sufi, and Trebbi (2014). More explicitly, Mian, Sufi and Trebbi (2010) focus on the legislative response to the financial crisis pre-dating the Dodd-Frank Act, while Kaiser (2013) offers an interesting and detailed discussion of the congressional evolution of the Dodd-Frank Act. Finally, the regulatory rule-making of Dodd-Frank is fully explored from a systematic empirical perspective by Bertrand, Bombardini, and Trebbi (2015).

The remainder of this paper is organized as follows. In Section 2 we provide a brief history of the Volcker Rule, as way of motivating our analysis through a most salient example. In Section 3 we discuss the main empirical measures, the variables construction, and provide a descriptive analysis of our samples. In Section 4 we discuss our econometric model and single breakpoint/multiple breakpoint testing in dynamic factor models. Our main empirical results on U.S. corporate bonds are reported in Section 5 and on Treasuries in Section 6. Section 7 concludes.

2 A Brief History of the Volcker Rule

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[7].

Throughout the summer and fall of 2009, the initial Treasury proposal were 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

[7]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

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[8]. 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 go into effect 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[9]. 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 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 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

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

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

trading desks[10]. Two days later, Goldman Sachs followed[11]. Several other banks such as Morgan Stanley, Bank of America, Citi Group, and RBC announced the shutdown of their proprietary trade desks one after another from January 2011 to April 2014, spanning the whole rulemaking period[12].

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 1 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[13]. In terms of the percentage of the total corporate bond outstanding, the decline is from more than 5% in 2007 to under 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 regulation 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. We also complement this approach with a standard difference-in-differences matching design around a salient regulatory event.

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

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

[12] 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.

[13] 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.

3 Data

3.1 U.S. Corporate Bonds Sample Description

The first main data set used for this paper is the Financial Industry Regulatory Authority's (FINRA) TRACE. This data currently provides transaction-level information of approximately 99% of all secondary corporate bond market transactions (not the primary offering). Trade reports are time stamped and include information on the clean price and par value traded, although the par value traded is truncated at $1 million for speculative grade bonds and at $5 million for investment grade bonds[14]. TRACE also reports whether a trade is a buy or sell, and whether a trade is between two dealers or between a dealer and a customer[15]. TRACE has expanded its coverage through three phases. In Phase I on July 1, 2002, FINRA began disseminating price and volume data for trades in selected investment-grade bonds with initial issue of $1 billion or greater, and 50 high-yield securities disseminated under FIPS. Phase II, implemented on April 14, 2003, expanded dissemination to smaller investment grade issues, bringing the number of bonds to approximately $4,650$. Finally, Phase III, implemented completely on February 7, 2005, required reporting on approximately 99% of all public transactions. To obtain a balanced panel, our sample covers the post Phase III period, April 1, 2005 to December 31, 2014, which covers essentially all the U.S. corporate bonds. We filter out erroneous trades following Dick-Nielsen et al. (2012).

We merge the cleaned TRACE transactions to bond characteristics provided by FISD. This data provides bond-level information such as issue date, issuance size, coupon rate, maturity date, credit ratings, underwriter identity and roles. Following Dick-Nielsen et al. (2012), we limit the sample to fixed-rate bonds that are not callable, convertible, putable, or have sinking fund provisions. We drop bonds issued more than 10 years ago, since these old bonds present very few transactions. Since our goal is to provide the most comprehensive coverage of U.S. corporate bond market, we keep bonds with semi-annual coupons because they are the most common bonds in the U.S. This is different from Dick-Nielsen et al. (2012), who keep the no-coupon bullet bonds. The raw TRACE data contains $34,422$ bonds. After applying the above filters, our final sample contains $18,632$ semi-annual coupon bonds. In comparison, Dick-Nielsen et al. (2012) cover $5,376$ bullet bonds.

Using the underwriting information from FISD, we can link each bond to its lead underwriters. There are several issues that need addressing. First, FISD does not provide

[14] Non-truncated trade volume is provided in "TRACE enhanced", a new version of TRACE. However, "TRACE enhanced" has 18 months of time lag in disseminating.

[15] In a regulatory version of TRACE used by Goldstein and Hotchkiss (2007), it can be directly identified whether the dealer for a given trade is a member of the underwriting syndicate for that bond. However, such information is not available in the public version.

a unique identifier for each underwriter. Instead, whenever an underwriter changes name, FISD creates a new ID. For example, "J P Morgan Securities Incorporated" and "J P Morgan Securities LLC" are assigned two different IDs. The second problem is that FISD underwriters are typically at the subsidiary level. For example, after Bank of America acquired Merrill Lynch in 2008, there are still bonds underwritten by Merrill Lynch, while the number of bonds underwritten by Bank of America goes down to zero. To create a consistent time series measure for each underwriter, we standardize the name provided by FISD and create a new ID for each underwriter. We further assign bonds issued by subsidiaries to the corresponding holding companies. Lastly, we combine two merged identities to compute the pre-merger liquidity measures to maintain a balanced bond portfolio.

We first construct liquidity measures for each corporate bond in our sample. Then we aggregate the bond-level liquidity to underwriter-level and aggregate-level. For the underwriter-level sample, we calculate the equal weighted average by bond rating group (investment-grade v.s high-yield) and issue size (above \$1 billion v.s. below \$1 billion) for each underwriter. Since smaller underwriters only underwrite a limited number of bonds, this makes the underwriter-level measure of liquidity quite noisy. Therefore, we keep the top 4 biggest underwriters, Bank of America (Merrill Lynch), JPMorgan Chase, Morgan Stanley and Goldman Sachs, and combine the rest into a residual "Others" group. In our analysis on the bankruptcy of Lehman Brothers and the takeover of Bear Stearns, we separate these two banks from the "Others" group.

3.2 Corporate Bonds Liquidity Measures: Construction

We first construct the following nine measures of liquidity for each corporate bond in our sample. Then we calculate the equal weighted average for each underwriter[16]. All measures below are decreasing in the level of liquidity. Some measures require a minimum number of trades to compute. This leads to many missing observations for some thinly traded bonds. To avoid introducing noises into our underwriter-level measure, we drop those measures for a bond if more than 25% of observations are missing[17]. For those measures with less 25% missing observations, we back fill the missing observations with lagged values.

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 et al. (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

[16] We also experimented with value-weighted averages with similar results to the ones reported below.

[17] We still keep other measures of the same bond, because requiring all the measures to be non-missing is overly restrictive.

$) 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 $N_{i,t}+1$ 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). Feldhutter (2012) 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:

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

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 spreads. We follow Dick-Nielsen et al. (2012) in the construction of the Roll measure. The Roll measure is defined as two times the square root of the negative covariance between two consecutive daily returns $r_{i,t}, r_{i-1,t}$ in month t. If the covariance is negative, the covariance is replaced with zero.

$$Roll_t = 2\sqrt{-Cov\left(r_{i,t}, r_{i-1,t}\right)}$$

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. Corporate bond spreads. The corporate bond spread is defined as the difference between corporate bond yields and a Treasury bond with the same maturity. The Treasury yields are obtained from Gürkaynak et al. (2007). We exclude bonds with less than 2 years or more than 30 years to maturity following Dick-Nielsen et al. (2012).

6. Turnover (negative). The annualized turnover for month t is defined as follows:

$$Turnover_t = \frac{Total\ Trading\ Volume_t}{Bond\ Issue\ Size} \times 12.$$

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.

3.3 U.S. Treasuries Sample Description

We use the CRSP Treasury database to construct our liquidity measures for the U.S. Treasury market. The daily data file is used to construct the Roll measure, and the monthly data file is used to construct the on-the-run premium.

We restrict our analysis to the same period as our corporate bond sample, April 1, 2005 to December 31, 2014. Our sample consists of Treasury bills, notes, and bonds that are noncallable, nonflowering, and with no special tax treatment. We also drop observations with obvious pricing errors such as negative prices. Treasury securities with remaining maturity less than 30 days are also dropped because of potential liquidity problems. After applying the filters, our final sample contains $1,124$ bonds. In addition to bond prices, we obtain the total Treasury trading volume from Securities Industry and Financial Markets Association (SIFMA), and the total public debt outstanding from Bloomberg.

3.4 Treasury Liquidity Measures: Construction

1. Yield curve fitting noise

Hu et al. (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[18].

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 by comparing an on-the-run issue to a synthetic off-the-run Treasury security with the same coupon rate and maturity date[19]. The yield of the synthetic off-the-run Treasury security is computed from the off-the-run yield curve constructed by Gurkaynak et al. (2007). The on-the-run premium is defined as the difference between the yield of this synthetic off-the-run bond and the on-the-run bond.

$$\begin{aligned} &\textit{on-the-run premium}_t \\ &= \textit{off-the-run yield}_t \ - \ \textit{on-the-run yield}_t. \end{aligned}$$

3. Roll measure and 4. Turnover (negative)

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

3.5 Summary Statistics and Descriptives

Figure 2 reports the full timeline of events relevant to our analysis. The summary statistics of the aggregate-level liquidity measures of the U.S. corporate bonds for the period April 2005 to December 2014 are reported in Table 1.

The corporate bond market is very illiquid compared to the equity market. For a typical bond, there is no single trade on 61% of business days. The annualized turnover rate is only 40%. In comparison, stocks in NYSE have a turnover ratio of 92% in December 2014[20].

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

[19] Some authors measure the on-the-run premium relative to the first or second off-the-run security, but this method introduces bias since those off-the-run issues will have shorter duration. The bias will become more significant in recent years when the yields were very low.

[20] See http://www.nyxdata.com/nysedata/asp/factbook/
for the historical trading volume of NYSE stocks.

Among all the trades, only 5% are block trades.

In such an illiquid market, finding a trading counterparty can be occasionally difficult. For this reason, typically corporate bond investors rely on specialized dealers to make the market rather than computerized trading platforms (as for example for Treasuries). Dealers usually hold certain amounts of inventories and use them to absorb temporal mismatches of supply and demand. As compensation for this service, dealers charge substantial fees for providing liquidity.

To get a quantitative assessment, one can compare various trading cost measures to credit spreads, the compensation for investors to bear the credit and liquidity risk of corporate bonds. The average credit spread of a U.S. corporate bond over a Treasury bond is 2.20% over our sample period. In comparison, the mean Amihud measure, which is based on the impact of $1 million dollar trade, is 0.95%, as reported in Table 1. This amounts to roughly half of the average credit spread earned in a year. The average IRC, which measures the cost charged by dealers in a round-trip trade, is 0.70%. This equals to a third of the average credit spread. The average Roll measure is 1.57%, which implies a bid-ask spread as large as three-fourth of the average credit spread.

Additionally, investors face high uncertainty in trading cost when executing their trades, as shown by a high time series variability of the Amihud and IRC measure. In synthesis, Table 1 shows that the U.S. corporate bond market is typically not particularly liquid. In this respect, the a priori concerns of public commentators of the effects of regulatory intervention on market liquidity were well placed.

In Table 2 we report the monthly linear correlations for each pair of liquidity proxies, to show consistency across our nine different measures of liquidity. Correlations are typically positive and sizeable. A partial exception is the Non-block trades measure, which we will discuss further below.

In Table 3, we provide more information on the liquidity for different underwriters (Bank of America, Goldman Sachs, JP Morgan Chase, Morgan Stanley, and all Others), issue sizes (large and small), and credit ratings (high-yield vs. investment-grade). This provides a total of 180 ($= 9 \times 5 \times 2 \times 2$) disaggregate liquidity series. On average, large-size issues are more liquid than small-size issues, and high-yield bonds are more liquid than investment-grade ones. The reason why investment-grade bonds are generally less liquid is that their main buyers are buy-and-hold investors, such as banks, insurance companies and pension funds, while high-yield bonds attract more credit hedge funds, which trade more frequently. There is some dispersion in liquidity across underwriters, which come from two sources. First, the bond characteristics of different underwriters can differ. Second, different underwriters may charge different fees in making markets, depending on their balance sheet capacity, risk appetite, market power, etc.

Figure 3 plots the underwriter-level liquidity measures for the four biggest underwriters: Bank of America (which includes Merrill Lynch both before and after September 2008 for consistency), Goldman Sachs, JP Morgan Chase, and Morgan Stanley, which accounts for 40% of market share plus a cumulate of all other remaining bonds ("Others" category). For ease of representation we aggregate the data across issue size and credit rating, in order to report a single time series for each underwriter and each liquidity proxy. The key observation is a strong co-movement among these time series. All liquidity measures spiked during the 2008-2009 financial crises, indicating liquidity depletion, but most of them have recovered since, with one partial exception: Non-block trades post-2009[21]. In our later analysis, we will explore the rich information in both the aggregate-level and underwriter-level measures.

4 Econometric Model

Our goal is to formally test for structural breaks in the market liquidity of fixed-income assets in the aftermath of the financial crisis, possibly pinning down the role of regulation by matching estimated breakpoints with the exact timing of regulatory reform. We present here the econometric setup that we are going to employ.

As anticipated in Section 3 we take both an aggregate-level and a disaggregate perspective in our analysis. We also refer to the latter as "underwriter-level" analysis. Let us define the matrix Y of L aggregate (i.e. market-level) liquidity measures observed for T periods. Y is of dimension $(T \times L)$. With the term "aggregate" liquidity measure we mean a measure of liquidity (such as those listed in Subsection (3.2)) that aggregates all securities in a market irrespective of identity of the underwriter, issue size, or credit rating. Although intuitive, this approach may mask heterogeneity in the dynamics of different types of securities. Therefore, in order to allow our methodology to identify specific structural breaks that might arise only within particular classes of securities or only for bonds where markets are made by specific underwriters/banks, we will refer to disaggregate liquidity measures as the matrix X of $N > L$ liquidity measures observed for T periods. X is of dimension $(T \times N)$ where

[21] Intuitively, during the financial crisis as market liquidity dried up, it became ingreasingly difficult to execute large trades (i.e. block trades). Investors had to break up their trades into smaller portions, either to avoid excessive price movements or because dealers suddenly became less willing to take on large positions. Non-block trades frequency increased as a consequence. This measure however does not appear to have recovered since the financial crisis. Anecdotal evidence suggests that this may be due to a concurrent change in the investor population. After the crisis, more and more bond mutual funds and ETFs, which behave differently from the traditional group of investors in terms of trade sizes, appear to have entered the market.

each column measures liquidity grouping bonds at the level of

$$(\textit{identity of the underwriter} \times \textit{issue size} \times \textit{credit rating}).$$

As a matter of accounting, recall that for our case we have $L = 9$ measures, 4 major underwriters plus 1 for the residual Others, 2 types of issue sizes (small or large), 2 types of credit rating (high yield and investment grade), hence $N = 180$. Our sample covers $T = 117$ months.

To the direct question of whether regulatory intervention has produced structural breaks in the *level* of liquidity, in either Y or X, standard tests for multiple breakpoint estimation (Bai and Perron, 1998, 2003) will be employed.

To the deeper question of whether the *underlying structure of correlation and of latent dynamics* of liquidity across different assets have indeed structurally changed, we will employ a more innovative approach through dynamic factor modeling of X, assessing structural breaks in factor loading or in unobserved factors. Such methodologies are more recent and deserve a more complete discussion, which we provide below. This discussion will be also helpful in briefly recalling the main features of some standard approaches in structural break estimation.

4.1 Dynamic Factor Model

This section introduces the basic notation, econometric setup, and follows the exposition in Chen et al. (2014), to which we refer for a detailed discussion of the proofs and the Montecarlo evidence of power and size of the tests. Consider a set of N observed liquidity measures constructed as in Section 3 and observed for $t = 1, ..., T$ periods, say, at monthly frequency. The matrix of observed underwriter-level variables[22] X of dimension $(T \times N)$ is expressed as function of r unobserved factors F of dimension $(T \times r)$, a matrix Λ of factor loadings of dimension $(N \times r)$, and a matrix of idiosyncratic errors ε of dimension $(T \times N)$. As typical in the literature, we have in period (row) t:

$$X_t = \Lambda F_t' + \varepsilon_t. \tag{1}$$

This formulation accommodates flexibly several possible latent structures: r static factors; or $\tilde{r}$ dynamic factors and $p = r/\tilde{r} - 1$ lags; or an arbitrary combination of static and dynamic factors and lags (Stock and Watson, 2011).

[22] For the dynamic factor model analysis let us indicate with an abuse of notation X as the matrix of first differenced and normalized liquidity measures, as indicated by Stock and Watson (2011).

Due to their flexibility in accommodating general dynamics across correlated time series, large factor models have enjoyed substantial success in the macroeconomics and finance literature. Stock and Watson (2002) show that the latent factors are consistently estimable by principal component analysis (PCA), an approach we follow here. PCA allows to estimate the r factors of X :

$$\hat{F}_t \equiv \left[\hat{F}_{1t}, \hat{F}_{2t}, ...\hat{F}_{rt}\right]$$

by focusing on the first r largest eigenvalues of the matrix XX' in the case $T \leq N$ (or of the matrix $X'X$ in the case $T > N$) and selecting the (appropriately orthogonalized and normalized) corresponding eigenvectors. Following Chen et al. (2014) we also define $\hat{F}_{-1t} \equiv \left[\hat{F}_{2t}, ...\hat{F}_{rt}\right]$.

The integer number of factors r has to be estimated, as the true number of factors is unknown. Let us indicate with $\hat{r}$ such estimated value over the full sample.

To this goal we employ ten different estimators, some with better finite sample properties than others, with the aim of providing an exhaustive range of $\hat{r}$'s. Eight of the estimators we employ follow the popular information criteria (IC) proposed by Bai and Ng (2002), including their preferred IC_{p1}, IC_{p2}, PC_{p1}, and PC_{p2}. IC estimators, however, can occasionally display in finite samples a somewhat undesirable dependency on one specific parameter necessary to the estimation: the maximum number of admissible factors in the model (typically indicated as $kmax$). This may occasionally lead to overestimation of the true number of factors (Ahn and Horenstein, 2014). It is also the reason we additionally employ the recent ER (eigenvalue ratio) and GR (growth ratio) estimators of Ahn and Horenstein (2014), which do not share this drawback and, by focusing on the ratio of subsequent eigenvalues (or the ratio of their logs), also hinge on the straightforward intuition of principal component analysis screeplots (i.e. a popular graphical representation of the progressive explanatory power of each principal component ranked by size of its eigenvalue). We take under consideration the range of number of factors between the minimum and the maximum of $\{IC_{p1}, IC_{p2}, IC_{p3}, PC_{p1}, PC_{p2}, PC_{p3}, AIC_3, BIC_3, ER, GR\}$, allowing for at least $\hat{r} = 2$ unobserved factors (a necessary condition for the statistical tests below).

4.2 Single Breakpoint Testing

We now proceed in introducing structural breaks in (1) and focus initially on the methodology for testing a single breakpoint, leaving multiple breakpoints to Section 4.3. It is relevant first to specify whether one is interested in breaks in the factor loadings Λ or in the factors

F. Let us begin by representing a single structural break in all factor loadings at date τ:

$$X_t = \Lambda F_t' + \varepsilon_t \quad t = 1, ..., \tau \tag{2}$$

$$X_t = \Gamma F_t' + \varepsilon_t \quad t = \tau + 1, ..., T \tag{3}$$

where Γ is the post-break matrix of factor loadings of dimension $(N \times r)$. An important insight of Chen et al. (2014) is that (2)-(3) can be represented as

$$X_t = \Lambda F_t' + \Delta G_t' + \varepsilon_t \tag{4}$$

where $\Delta = \Gamma - \Lambda$ measures the change in the loadings and

$$G_t = 0 \quad t = 1, ..., \tau$$
$$G_t = F_t \quad t = \tau + 1, ..., T.$$

The notation so far has focused on a single structural breakpoint for all r factors. At a given breakpoint, Chen et al. (2014) distinguish between two types of breaks: small and large. Consider k_2 small breaks, of the type discussed by Stock and Watson (2002, 2009). These are defined as local-to-zero instabilities in the factor loadings that asymptotically average out without affecting estimation and inference under PCA. These are not the type of breaks we are interested in. In the context of large policy shifts, one is most likely interested in big structural breaks, indicated as $k_1 = r - k_2$. The formal definition is given in Chen et al. (2014), but more importantly it is proven that under k_1 big breaks in (4), $\hat{F}_t$ estimated by PCA delivers inconsistent estimates of the space of the original factors F_t. Instead, defining G_t^1 the partition of G_t corresponding to the large breaks only, the full sample PCA delivers consistent estimates of the space of the new factors $[F_t \; G_t^1]$. Specifically, over the full sample the number of factors tends to be overestimated by k_1. Chen et al. (2014) prove that a factor model with r unobserved factors and with $0 < k_1 \leq r$ big structural breaks in the factor loadings at time τ admits a representation with (asymptotically) $r + k_1$ factors. Particularly, given an IC estimator in Bai and Ng (2002) $\hat{r}$ and under general assumptions, it is shown (Proposition 2, p.34):

$$\lim_{N,T\to\infty} \mathbb{P}\left[\hat{r} = r + k_1\right] = 1. \tag{5}$$

An important remark at this point is to notice that if the break date τ were known, one could recover a consistent estimate of r by simply splitting the sample in a "before-breakpoint" and "after-breakpoint" subsamples and performing PCA and Bai and Ng (2002) or Ahn and Horenstein (2014) in either subsample. In either case,

$$\lim_{N,T\to\infty} \mathbb{P}\left[\hat{r}_{before} = r\right] = 1$$
$$\lim_{N,T\to\infty} \mathbb{P}\left[\hat{r}_{after} = r\right] = 1.$$

both $\hat{r}_{before}$ and $\hat{r}_{after}$ typically lower than the full sample estimate $\hat{r}$.

For the sake of generality, we take the exact breakpoint date τ as unknown. Although we explicitly consider the exact date of the finalization of the Volcker Rule in the difference-in differences matching below, the possibility of anticipatory behavior or of delayed response for a policy intervention so sizeable and publicly debated would caution against a 'known breakpoint' approach. Hence, we do not impose such restriction here.

Chen et al. (2014) present a test for the null $H_0 : k_1 = 0$ versus the alternative of at least one big break $H_1 : k_1 > 0$ based on detecting breaks in $\hat{F}_t$ estimated over the full sample by PCA. The implementation is straightforward. Define $\hat{\beta}$ the estimated $(\hat{r}-1)\times 1$ coefficient vector obtained by regressing $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ and $\hat{S}$ its corresponding Newey-West HAC covariance matrix[23]. One can test for structural breaks in β by focusing for the case of unknown breakpoint $\tau = T\pi$ with $\pi \in \Pi \equiv (\pi_0, 1-\pi_0)$ and $0 < \pi_0 < 1$ based on Andrews (1993) Sup-Wald statistic or Sup-LM statistic. Specifically, for given τ, and hence $\pi = \tau/T$, define $\hat{\beta}_1(\pi)$ the estimated $(\hat{r}-1)\times 1$ coefficient vector obtained by regressing $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ for $t = 1, ..., \tau$ and $\hat{\beta}_2(\pi)$ the estimated $(\hat{r}-1)\times 1$ coefficient vector obtained by regressing $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ for $t = \tau+1, ..., T$ the Sup-Wald statistic is:

$$\begin{aligned}\mathcal{L}^*(\Pi) = &\sup_{\pi\in\Pi} T\pi(1-\pi) \\ &\times \left(\hat{\beta}_1(\pi) - \hat{\beta}_2(\pi)\right)' \hat{S}^{-1}\left(\hat{\beta}_1(\pi) - \hat{\beta}_2(\pi)\right)\end{aligned} \tag{6}$$

and the Sup-LM statistic is:

$$\begin{aligned}\mathcal{L}(\Pi) = &\sup_{\pi\in\Pi} \frac{1}{\pi(1-\pi)} \\ &\times \left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T\pi}\hat{F}_{-1t}\hat{F}_{1t}\right)' \hat{S}^{-1}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{T\pi}\hat{F}_{-1t}\hat{F}_{1t}\right)\end{aligned} \tag{7}$$

In the analysis we will maintain a conservative $\pi_0 = 0.3$ which in our case is not overly restrictive as it allows a search for structural breaks between January 2008 and January 2012 covering the full financial crisis, the full legislative debate on Dodd-Frank and large

[23]Newey and West (1987). $\hat{S}$ is estimated over the full sample.

part of the regulatory rulemaking period for the Volcker Rule. We employ the critical values for the (6) and (7) statistics reported in Andrews (1993).

To conclude this subsection, let us consider the matter of detecting a structural break in the factors themselves as opposed to a break in the factor loadings at τ. There are at least two different formulations for a break in the factors one should consider. First, the formulation discussed in Chen et al. (2014) considers maintaining unvaried the loadings Λ, but changing the variance-covariance matrix of the r original factors:

$$\mathbb{E}\left[F_t F_t'\right] = \Sigma \quad t = 1, ..., \tau \tag{8}$$

$$\mathbb{E}\left[F_t F_t'\right] = \Xi \quad t = \tau + 1, ..., T \tag{9}$$

where Σ is the factor covariance before the break and Ξ after the break and both are $(r \times r)$. Given that the approach above focused on testing breaks in the $\hat{F}_t$ PCA factors estimated over the full sample, it may not appear surprising that the Sup tests above (based on regressing $\hat{F}_{1t}$ on $\hat{F}_{-1t}$) will be naturally able to pick up breaks of the type (8)-(9). In fact, the same regression approach described above will reject the null of big breaks in presence of changes in factors.

It is possible however to discriminate between breaks in loadings and breaks in factors by noticing that in the case of breaks in factors:

$$\lim_{N,T\to\infty} \mathbb{P}\left[\hat{r} = r\right] = \lim_{N,T\to\infty} \mathbb{P}\left[\hat{r}_{before} = r\right] = \lim_{N,T\to\infty} \mathbb{P}\left[\hat{r}_{after} = r\right] = 1.$$

This implies that in the case of breaks in the factors typically $\hat{r}$ estimated over the whole sample will be identical as when estimated on subsamples either before or after the breakpoint. In the case of breaks in the loadings, instead, $\hat{r}$ estimated over the full sample will be higher than when estimated on subsamples either before or after the breakpoint, as evident from the result in (5).

A second formulation for a break in the factors is more drastic and entails a break in the number of factors r in (1), that is the addition or subtraction of specific factors in the model at date τ. Differently from the formulation discussed in Chen et al. (2014), for the detection of this type of breaks one cannot rely on a comparison between the whole sample $\hat{r}$ and any of the two subsample estimates $\hat{r}_{before}$ and $\hat{r}_{after}$. Rather we need to rely on directly comparing $\hat{r}_{before}$ and $\hat{r}_{after}$ themselves. Given a consistent estimate of the breakpoint τ, any difference in the number of estimated factors $\hat{r}_{before}$ and $\hat{r}_{after}$, which are consistent estimates of the rank of the factor space within each subsample, is indication of a break in (1).

4.3 Multiple Breakpoint Testing

Let us now focus on multiple structural breaks M in factor loadings at unknown dates $\tau_1, \tau_2, ..., \tau_M$. This structure partitions the sample period of length T in $M+1$ intervals:

$$
\begin{aligned}
X_t &= \Lambda F_t' + \varepsilon_t \quad t = 1, ..., \tau_1 \\
X_t &= \Gamma^1 F_t' + \varepsilon_t \quad t = \tau_1 + 1, ..., \tau_2 \\
&... \\
X_t &= \Gamma^M F_t' + \varepsilon_t \quad t = \tau_M + 1, ..., T
\end{aligned}
$$

where Γ^m with $m = 1, ..., M$ are the post first break matrices of factor loadings of dimension $(N \times r)$. In the context of multiple breakpoints, standard estimators in the literature include the ones proposed by Bai and Perron (1998, 2003), which we employ in combination to the regression approach delineated in Section 4.2. Considering the regression of $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ with the goal of detecting not one, but multiple breakpoints, we implement the recommended approach of Bai and Perron (1998, 2003).

Consider for the interval $t = \tau_m+1, ..., \tau_{m+1}$ the regression of $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ in this subsample and call the estimated coefficient $\hat{\beta}_m$. Notice that, like $\hat{\beta}_1(\pi)$ and $\hat{\beta}_2(\pi)$ in Section 4.2, $\hat{\beta}_m$ depends on the breakpoint parameters, $\pi_m = \tau_m/T$ and $\pi_{m+1} = \tau_{m+1}/T$. Given M, let us also define $\hat{\beta} = \left(\hat{\beta}_1', \hat{\beta}_2', ..., \hat{\beta}_{M+1}'\right)'$. Bai and Perron (1998) first consider the Sup-F type test of the null hypothesis of no structural break $(M = 0)$ against the alternative hypothesis that there is a known number of breaks $M = k$:

$$
\begin{aligned}
&\sup_{(\pi_1,...,\pi_k)} F_T(\pi_1, ..., \pi_k; r-1) \\
&= \frac{1}{T}\left(\frac{T-(k+1)(r-1)}{k(r-1)}\right)\hat{\beta}' R' \left(R\hat{S}R'\right)^{-1} R\hat{\beta}
\end{aligned}
$$

where R is the matrix such that $\left(R\hat{\beta}\right)' = \left(\hat{\beta}_1' - \hat{\beta}_2', ..., \hat{\beta}_k' - \hat{\beta}_{k+1}'\right)$ and $\hat{S}$ is now an estimated HAC variance covariance matrix of $\hat{\beta}$ [24].

As the number of breaks is unknown, a second type of test is more useful: Bai and Perron (1998) consider a test of the null hypothesis of no structural break $(M = 0)$ against the alternative hypothesis that there is an unknown number of breaks $M = m$ with m

[24] In the tests we perform we apply a short trimming of 10%. The Bai and Perron requires a minimal admissible distance expressed as fraction of T among any pair of breakpoints τ_m and τ_{m+1} and we set it to 10% of the sample length, in order to allow for relatively close multiple breaks. In all the test we also allow the distribution of ε_t to vary across different intervals.

ranging between 1 and $\bar{m}$, which is given[25]. The test is referred to as the double maximum test and two different statistics are employed:

$$
\begin{aligned}
& UD\max F_T(\bar{m}; r-1) \\
& = \max_{1\leq m\leq \bar{m}} \sup_{(\pi_1,...,\pi_k)} F_T(\pi_1, ..., \pi_k; r-1)
\end{aligned}
$$

which is unweighted with respect of each break number, and

$$
\begin{aligned}
& WD\max F_T(\bar{m}; r-1, a_1, ..., a_{\bar{m}}) \\
& = \max_{1\leq m\leq \bar{m}} a_m \times \sup_{(\pi_1,...,\pi_k)} F_T(\pi_1, ..., \pi_k; r-1)
\end{aligned}
$$

which is a weighted version, where weights are defined such that the marginal p-values are equal across values of m [26].

The final test proposed by Bai and Perron is a sequential test. One proceeds by testing ℓ breaks against $\ell+1$ breaks. The test is commonly labelled $\sup F_T(\ell+1|\ell)$ and intuitively is built as follows. Consider the $\ell+1$ intervals generated by the ℓ break points under the null hypothesis. Within each interval a separate test of the type $\sup_{(\pi_1)} F_T(\pi_1; r-1)$ is run, i.e. a test of the null hypothesis of no break versus the alternative hypothesis of 1 break. The test rejects the null hypothesis in favor of $\ell+1$ breaks if, relatively to the sum of squared residuals obtained under the ℓ breaks model obtained by regressing $\hat{F}_{1t}$ on $\hat{F}_{-1t}$ and aggregated across all intervals, there is one additional break that produces a sum of squared residuals sufficiently smaller under the $\ell+1$ breaks model.

Bai and Perron (2003) recommend to first obtain both the $UD\max F_T(\bar{m}; r-1)$ and $WD\max F_T(\bar{m}; r-1, a_1, ..., a_{\bar{m}})$ to test whether at least one break is detected in the entire sample, as these tests are more prompt in rejecting the null hypothesis in presence of multiple but contiguous breaks (e.g. which would be the case for instance if there were a break at the beginning of the crisis and one at its end). If at least one break is detected, then the sequential approach should be employed. Specifically one should select $M = m$ such that $\sup F_T(\ell+1|\ell)$ are insignificant for $\ell \geq m$. We follow this approach here.

[25] In the tests we perform we allow for a maximum of $\bar{m} = 5$ total breakpoints (which, as shown below, will prove to be sufficiently high and is also the value suggested in Bai and Perron, 2003).

[26] Specifically $a_1 = 1$ and $a_m = c(r-1, \alpha, 1)/c(r-1, \alpha, m)$, for $m > 1$, where α is the significance level of the test and $c(r-1, \alpha, m)$ is the asymptotic critical value of the corresponding Sup-F test for m breaks, which is reported by Bai and Perron (1998, 2003).

5 Results for Market Liquidity of U.S. Corporate Bonds

For U.S. corporate bonds we present four different estimation strategies. We will begin by applying multiple breakpoint tests to measures of market liquidity provisions.

Subsequently we will focus on a dynamic factor model and presents results of both single and multiple breakpoints in factor loadings, with the understanding that also further testing for factor breaks is available.

Finally we will focus on difference-in-differences matching results. A final analysis of the cases of bonds underwritten by Lehman Brothers and Bear Stearns will conclude the section.

5.1 Multiple Breakpoint Tests for Liquidity Levels and Liquidity Risk

We begin by studying break in means of our main nine liquidity measures (or properly seven measures of liquidity levels and two measures of liquidity risk) employing the Bai and Perron (1998, 2003) estimation approach for multiple unknown breakpoints in the undifferenced and unstandardized time series. At the onset we will not separate bonds by underwriter, issue size, and credit rating. Rather we aggregate all bonds and plot their time series in Figure 4. These nine aggregate time series do not behave much differently than their more disaggregate counterparts in Figure 3, but given their more manageable number, are amenable of more careful discussion. The estimated means for each sub-period (red line) are also reported, where the break dates are estimated by the Bai and Perron (1998-2003) approach and are breaks significant at the 5% confidence level.

Table 4 presents the estimated breakpoints in the mean at the 5% confidence levels for Amihud, Amihud (standard deviation), IRC, IRC (standard deviation), Roll measure, Non-block trade, Spread, Turnover (negative), and Zero trading frequency. The corresponding double maximum tests for the simple breaks in means of the liquidity proxies are reported in Table 5. This table indicates the presence of at least a structural break at the 5% confidence level in all nine proxies, with the exception of the $UD\max$ for the Spread variable. However, for the same variable $WD\max$ reject the null that there is no break. Concerning the dating of the structural breaks, a reasonable prior would be picking up at least the drastic reduction in liquidity produced by the near collapse of the U.S. financial system in September 2008 and the subsequent break towards more normal market liquidity levels at the end of 2009 (see Figure 3). Any detection of subsequent structural breaks towards lower levels of liquidity over the periods 2010-2014 should instead be carefully examined, as potential telltale sign of liquidity depletion concurrent with and possibly caused by regulatory intervention.

The sequential $\sup F_T(\ell + 1|\ell)$ indicates three breakpoints for the IRC, IRC (standard deviation), Roll measure, Non-block trades, and Zero trading; one for the Amihud, Amihud (standard deviation), and Spread; four for the Turnover (negative)[27]. As clarified by Figure 4, the Bai-Perron approach indicates clearly intuitive breaks in liquidity around the financial crisis. None of the structural breaks happen during the period of regulatory intervention around the approval of Dodd-Frank, at the time of major banks shutdowns of proprietary trading desks, or at the time of the approval of the proposed or the finalized Volcker Rule.

While this is prima facie evidence against drastic reductions in liquidity following regulatory intervention, it is still possible that at the level of specific types of corporate bonds structural breaks may arise. In Figure 5 we present a graph tracing for each month the fraction of our 180 underwriter-level market liquidity variables that are described to have a statistically significant (at 5% confidence level) break in that month and in what direction (i.e. towards lower liquidity -in blue- or higher liquidity -in red).The bulk of the structural breaks toward lower liquidity happens in July and August 2008, right before Lehman Brothers' failure. As it appears clear in Figure 5, if anything, around subsequent periods of regulatory intervention the disaggregate liquidity measures pointed systematically toward higher liquidity, not lower.

To understand the source of the disaggregate-level structural breaks, Figure 6 shows the decomposition of break dates by underwriting bank. We can see that the bankruptcy of Lehman Brothers in September 2008 caused similar liquidity reductions for all underwriters. In comparison, the later recoveries are more heterogenous: bonds underwritten by JP Morgan and Goldman Sachs experienced earlier recovery in liquidity than bonds of other underwriters. This is consistent with anecdotal evidence that these two banks had relatively stronger balance sheets throughout the crisis.

The most important observation from this graph, however, is from the later period when banks start to shutdown their proprietary trading desks after the passage of the Dodd-Frank Act. Were proprietary trading indispensable for market making, one would expected to see bank-specific liquidity reductions line up with an announced trading desk shutdown by the same bank. This is hardly the case: no large bank specific liquidity reduction is observed after 2010 (all the bank-specific frequencies of liquidity reduction are below 5% after 2010). On the contrary, many banks experience liquidity increases around July 2012, in the midst of regulatory interventions[28]. There appears to be no clear evidence that the shutting down of proprietary trading desks was associated with an adverse impact on market liquidity.

Figure 7 further breaks down all the structural breaks by bond type. This graph reveals

[27] In Appendix we report the relevant statistics for the sup $F_T(\ell+1|\ell)$ tests.

[28] A gradual shutdown of the trading desk would not be a problem for our test, since the estimated break points will show up sometime after the announcement date. However, we see none of this lagged liqudity reduction.

more heterogeneity in the cross-section. The liquidity reductions in high-yield bonds, a sign of trouble in the financial sector, preceded investment-grade breaks before the crisis. The subsequent recovery of high-yield bonds (around July 2012) appears also much slower than the investment-grade (around January 2010). Interestingly, investment-grade bonds experienced large illiquidity spikes in the middle of the crisis. This is probably because the main clientele of investment-grade bonds, banks and insurance companies, were hit particularly hard by the shock of Lehman Brothers bankruptcy. Similar patterns can also be found in the comparison between large-size bonds and small-size bonds. During the period of regulatory intervention, the only series that exhibits relatively large liquidity reductions is the large-size bonds during November 2011. However, their liquidity seems to recover immediately afterwards, as shown by several breaks towards higher liquidity following the initial reduction.

Since different measures proxy different aspects of liquidity, in Figure 8 we break down all the structural breaks by measure. Amihud, Amihud (standard deviation), Roll measure and Spread experienced early illiquidity spikes during July 2007, when initial signs of trouble started to emerge in the housing market. When Lehman Brothers went bankrupt in September 2008, IRC, IRC (standard deviation) and Non-block trade had huge illiquidity spikes. During the later stage of crisis from December 2008 to May 2009, trading activities started to pick up, as shown by red spikes of Turnover (negative) and Zero trading. Recoveries in other liquidity measures soon followed. The only exception is Turnover (negative), which experienced several breaks towards lower liquidity after 2010. Although this measure seems to suggest liquidity deterioration post 2010, the caveat is that similar breaks also occurred as early as March 2006, a year before the start of crisis. In fact, using a subsample of bonds which allows us to extend the sample period to 2002, we are able to show that corporate bond turnover has been on a downward trend for more than ten years (this result is available upon request). The breaks in Turnover (negative) post 2010 could simply be a continuation of this downward trend.

Overall, from the decomposition of liquidity breaks, we can see an intuitive pattern of liquidity reductions at the onset of the financial crisis and liquidity increases in the recovery. During periods of regulatory intervention (2010-2014), with the possible exception of Turnover (negative), no systematic evidence of liquidity reduction is found for the whole cross-section of underwriters, bond type, and liquidity measures. The evidence in this subsection consistently supports the view that post-crisis U.S. regulatory intervention did not appear related to structural deteriorations in market liquidity.

5.2 Single Breakpoint Tests for the Dynamic Factor Model

This subsection shifts the attention to a dynamic factor model with the goal of assessing whether the underlying structure of correlation and of latent dynamics of liquidity across different bond types displays salient breaks during the period of crisis and post-crisis regulatory intervention. Rather than focusing on levels of liquidity or liquidity risk as in the previous subsection, we focus here on the underlying structure of autocorrelation and cross-dependence across a large set of liquidity measures. Detection of structural breaks in the factor structure of corporate bond liquidity around dates of regulatory intervention could in fact point to more subtle effects of regulation on market liquidity provision.

We discuss here the application of Chen et al. (2014) using the 2005-14 monthly sample and our full matrix X of $N = 180$ differenced and standardized underwriter-level time series. As reported in Figure 2, the presence of a long period of regulatory intervention between 2010 and 2015 with multiple potential points of structural change suggests a flexible approach, leaving the breakpoint date unknown.

A first preliminary step requires to estimate the number of factors over the full sample $T = 117$. According to our discussion in Section 4.2 this approach will not deliver a consistent estimate of the number of true factors in (1), but rather the sum of the true factors r and the number of big breaks in these factor loadings k_1. In Table 6 we report the full set of estimates based on Bai and Ng (2002) and Ahn and Horenstein (2014). Here we impose a $kmax = 10$ and notice that the estimates for $\{IC_{p1}, IC_{p2}, IC_{p3}, PC_{p1}, PC_{p2}, PC_{p3}, AIC_3, BIC_3, ER, GR\}$ range from 1 to 10. Although this is less than ideal for the goal of assessing the exact number of factors in the data, this is of little effect for the interpretation of our main findings in Figure 9.

Figure 9 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 $\pi_0 = 0.3$. 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. Figure 9 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 Table 6.

As evident from Figure 9, the Sup tests systematically pick breaks in factor loadings (at 5% confidence) when we allow a number of estimated factors above 3. 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 (such as the passage of the Dodd-Frank Act or the proposal of the Volcker Rule), but rather corresponds to dynamics within the financial crisis itself. In essence what the Chen et al. (2014) methodology allow us to exclude is that a structural break in the underlying factor structure of the underwriter-level liquidity occurred around dates of post-crisis regulatory activity.

In Table 7 we explore more in detail whether the structural breaks we observe can be attributed to breaks in the factor loadings of our model or to breaks in the factors themselves based on the discussion in Section 4.2. To maintain the presentation tractable, we focus here only on the ER estimates for the number of factors (potentially we could perform this exercise with all estimators in Table 6). We perform the ER estimation on the subsamples before and after the estimated breakpoints under the different models, allowing the number of factors on the whole sample to range from 2 to 10. The breakpoint dates are also reported in Table 7. With the exception of the case of 2 factors, the number of ER estimated factors $\hat{r}_{before}$ and $\hat{r}_{after}$ are typically different, with $\hat{r}_{before} = 2$ and $\hat{r}_{after} = 1$ for most models. This appears to suggest drastic breaks in the number of factors in (1), rather than breaks in the factor loadings Λ. Given the magnitude of the financial impact of the crisis, the presence of drastic changes in the liquidity factor structure in 2008-09 does not appears unreasonable.

So far 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 following subsection.

5.3 Multiple Breakpoint Tests for the Dynamic Factor Model

This subsection employs the Bai and Perron (1998, 2003) approach within the dynamic factor model, transposing the logic of Chen et al. (2014) to the multiple breakpoint setting.

Table 6 is still the reference for the allowed number of factors, a range which we will fully explore. Table 8 presents the estimated breakpoints in the factor loadings at the 5% confidence levels across different factor models ranging from $\hat{r} = 2, ..., 10$ estimated factors, employing the Bai and Perron (1998, 2003) preferred approach to the first $\hat{r}$ PCA estimated factors of the matrix X of differenced and standardize underwriter-level liquidity measures[29].

The corresponding double maximum tests for the breaks in the factor loadings are reported in Table 9. This table indicates the presence of at least a structural break at the 5% confidence level in nine out of ten dynamic factor models, with the exception of $\hat{r} = 2$ where both the $UD\max$ and $WD\max$ cannot reject the null that there is no break. The sequential $\sup F_T(\ell + 1|\ell)$ indicates at most two breakpoints for the models with $\hat{r} = 3, 4, 5, 6, 7$, all

[29]Given the small number of time series available for the analysis of liquidity of Treasuries we do not employ dynamic factor model approaches in this Section.

essentially coincident with the start and end of the recession and the financial crisis[30]. As in the previous section, such dating does not correspond to regulatory events of prominence (the passage of the Dodd-Frank Act in July 2010 or the announcement of the finalized Volcker Rule in January 2014), but rather appears to correspond to dynamics within the confines of the financial crisis itself.

With $\hat{r} = 8, 9, 10$, more breakpoints in the factor loadings appear, specifically around September 2010 and October 2011. These, however, as we have seen in Figure 5, are also dates of frequent breakpoints in means of liquidity measures pointing at liquidity increases, not liquidity reductions. With a sufficiently flexible $8-10$ factors model, the tests are likely picking up similar changes. While speculative, one likely explanation could be the ability of our model to pick up an increasing role for electronic trading and for open-end mutual funds[31].

In Table 10 we return to the issue of detecting breaks in factor loadings versus breaks in factors themselves across different subperiods. The subperiods are defined by the estimated breakpoints indicated in Table 8. As in Table 7, for tractability, we focus here only on the ER estimates for the number of factors. Under various models allowing a number of factors on the whole sample ranging from 2 to 10, we perform the ER estimation on all subsamples (up to a maximum of 6). For all models, we detect at least one breakpoint where the number of factors decreases or increases across adjacent subperiods, pointing at likely breaks in the factors. Differently from Table 7, such breaks in the factors are detected not just around the financial crisis, but also in 2010M9 and 2011M10 in two of the models ($\hat{r} = 8, 10$).

5.4 Difference-in-Differences Matching for Liquidity Levels and Liquidity Risk

We now present a more standard estimation strategy based on a difference-in-differences exercise augmented by matching of corporate bonds based on pre-treatment covariates (Heckman, Ichimura, Smith, and Todd, 1998; Smith and Todd, 2005). Here, for reason that will become clear in the construction of the test, we will focus only on the finalization of the Volcker Rule in January 2014 as our treatment date. Given the limitation in our "post" sample of just 12 months available, we will take a symmetric 12-month window around January 2014.

Relative to the analysis above, the approach of this subsection is more restrictive, as it focuses on a single regulatory dimension and relies on a difference-in-differences type of identification, but it is also an approach much more familiar to applied econometricians.

[30] In Appendix we report the relevant statistics for the $\sup F_T\,(\ell+1|\ell)$ tests.

[31] See Dudley (2015).

In addition, by relying on different identifying assumptions, complements nicely the macroeconometric estimation strategy above.

We proceed as follows. First, we manually classify the top 40 underwriters into two groups –one covered by Volcker Rule and the other not covered based on the revised finalized version of Volcker Rule[32]. Then we identify the set of bonds who have at least one underwriter not covered by the Volcker Rule, that is a non-banking entity for which proprietary trading is not restricted. This set of bonds is a useful benchmark as at least one of the underwriters who typically make market on that bond is virtually unconstrained by the main regulatory restriction in the rule, and hence virtually free to provide liquidity services in case banking entities were so impaired. For each of these $1,936$ non-Volcker Rule bonds that are traded between January 2013 and December 2014, we find a match among all the Volcker Rule bonds issued in the same quarter, that matures in the same year, has the same credit rating (investment grade/high yield), and has a relative size difference less than 50% of the average size of the pair[33]. If more than one bond satisfies the above criteria, we keep the one with smallest relative size difference. Since the Volcker Rule bonds are significantly larger than non-Volcker Rule bonds[34], many observations are dropped due to the last criterion on relative size. We ended up with a matched sample of 316 pair of bonds.

Table 11 reports the results for a difference-in-differences model for each of our nine liquidity proxies where the treatment is administered to the Volcker Rule bonds after January 2014 and each regression controls for a second order polynomial in issue age, bond fixed effects, and month fixed effects. Standard errors are two-way clustered at the bond and month level. In eight our of nine measures the treatment does not predict reductions in liquidity with a confidence level of 5%. Only for IRC (standard deviation) we find a statistically significant effect. This is not particularly worrying since only 50 non-Volcker Rule bonds have non-missing IRC (standard deviation) measure. Overall, there seems to be no robust evidence of liquidity depletion as consequence of the Volcker Rule.

The regression evidence is also supported by the graphical representation. In Figure 10 we show the time series of the Volcker Rule bonds and non-Volcker Rule bonds around the time when the revised finalized version of the Rule was approved (the vertical line, 2014M1). Both time series are normalized to take value of 0 at 2013M12. Were evidence of liquidity depletion present in the data, one would expect to see systematically higher levels of the blue line after the treatment, a sign of reduced liquidity or heightened liquidity risk. This

[32] See the the following document from Federal Register for details of the final rule: http://www.gpo.gov/fdsys/pkg/FR-2014-01-31/pdf/2013-31476.pdf

[33] There are fewer non-Volcker Rule bonds so we start our matching with them.

[34] In the unmatched sample, the average size of Volcker Rule bonds are 28 times larger than non-Volcker Rule bonds.

is hardly the case both in reporting unconditional time series as in Figure 10 or time series where bond and month fixed effects are conditioned out (not reported to save space).

As discussed above, the difference-in-differences matching approach restricts our analysis to a specific event and a small matched sample of bonds. One may wonder whether non-Volcker Rule bonds in general have higher liquidity than Volcker Rule bonds during periods of post-crisis regulatory intervention. A graphical representation of the data shows virtually no differential behavior by bonds underwritten by banks limited by the rule. In Figure 11 we compute the mean liquidity for all the $10,634$ Volcker Rule bonds and $4,673$ non-Volcker Rule bonds (instead of using the small matched sample) for each month, then report the difference between the mean liquidity of the two groups. Intuitively if both classes of bonds were equally liquid the lines should hover around zero. To this time series we also overlay the estimated breaks in means using Bai and Perron (1998, 2003) approach. Again in all measures, with the possible exception of IRC, we do not detect any differential deterioration in liquidity due to the proposed Volcker Rule passage (2011M7) or final rule passage (2014M1).

5.5 Sanity Check: Lehman Brothers

As highlighted in Figure 6, our approach allows for bank-specific breakpoint testing of all main liquidity measures. The reader interested in bank-specific liquidity breaks results, applying the Bai and Perron (1998,2003) approach to the undifferenced and unstandardized main liquidity measures may obtain them upon request. There is however a set of banks that deserve specific attention because the circumstances of their demise can help assessing the power of the tests we perform when comparing them to the rest of the market.

Consider the case of Lehman Brothers, the fourth largest investment bank in the country at the time of its bankruptcy on September 15, 2008. Lehman Brothers was a prolific underwriter and a case could be made for its failure producing an effect on the liquidity of the corporate bonds for which this bank was making markets. That is, Lehman's sudden demise should produce a sizeable drop in liquidity for bonds it had underwritten (corresponding to an increase across our nine (il)liquidity measures above and beyond the rest of the market).

Figure 12 shows the time series of liquidity differences between bonds underwritten by Lehman Brothers and other underwriters (blue line), and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The liquidity measures are constructed using only bonds underwritten before September 2008[35]. If the liquidity of the Lehman Brothers bonds matched

[35]Since Lehman Brothers stopped underwriting new bonds after its bankruptcy, and newly issued bonds are more liquid than the old ones, to make the comparision fair, we drop bonds issued by other underwriters after the bankruptcy of Lehman Brothers (September 2008) so that the liquidity deterioration of Lehman

exactly the liquidity of the rest of the market for that type of securities, all blue lines should be flat and hover around zero. Instead, for IRC, the Roll measure, Non-block trades, Turnover (negative), and Zero trading, Lehman Brothers-underwritten bonds strongly deteriorate in their liquidity relative to the rest of the market over time. Our methodology detects several significant structural breakpoints around the financial crisis. In addition, the Amihud measure also breaks towards lower liquidity in 2008 (but also shows a counterintuitive down-break in 2014). At least six out of nine measure of liquidity present behavior over time consistent with our approach and in five measures we are able to pick up a statistically significant structural break in relative liquidity around the appropriate date (Amihud, IRC, IRC sd, Roll, Non-block trades).

In Appendix Figure 1 we perform the same exercise for Bear Stearns, focusing there only on bonds underwritten before March 2008. Although early breaks are occasionally detected, the persistent illiquidity identified for Lehman Brothers is not present in the data. The fact that instead of failing, this bank was taken over by JP Morgan Chase is the most likely crucial difference for interpreting this finding, as most likely JP Morgan took over the market making on Bear Stearns underwritten bonds as well, muting the validity of our approach in this specific instance.

5.6 Comments on the Decline of Dealer Corporate Bond Inventories

With systematic evidence supporting the absence of structural breaks in corporate bond liquidity, we will now conclude this section by going back to the dramatic decline in dealer corporate bond inventories, which may appear counterintuitive.

We apply the Bai and Perron (1998, 2003) approach on this series, and overlay the estimated mean with the time series of the raw data in Figure 1. Three lessons can be learned from this test.

First, the estimation shows, as is obvious in observing the time series of the raw data, that the major reductions in dealer inventories occurred at the onset of the financial crisis (2008M10), far ahead of the initial proposal of the Volcker Rule. Therefore, at a minimum, there are other important factors driving the reductions of the inventories unrelated to the Volcker Rule.

Second, the abnormally high level of bond holdings in 2007 seems the result of a pre-crisis run-up of risk-taking, as shown by a series of breaks towards greater holding amounts between 2002 and 2007. In this light, the dramatic reduction during the crisis appears actually more

bonds is not driven mechanically comparing old bonds to new bonds.

a “getting back to normal”. In this sense, using the pre-crisis level as a baseline to calculate the change of inventory is somewhat misleading.

Third, there are two minor breaks, one in August 2011 and the other in March 2013, that fall into periods of regulatory intervention. However, as our tests on market liquidity have systematically shown, no structural reductions in market liquidity occurred during this period. This seems to suggest that not all the bonds held by dealers might be for liquidity-enhancing market-making[36]. Some of the holdings may be purely for risk-taking purposes, exactly the kind of activities that the Volcker Rule restrains.

6 Results for Market Liquidity of U.S. Treasuries

This section extends our analysis to the U.S. Treasuries market. Much of the interest and the discussion pertinent to this market's liquidity can be ascribed to the salience of events like the flash crash of October 15th, 2014 when the yield of the U.S. 10-year note dropped by 34 basis points from 2.2% to 1.86% in the eight minutes between 9:33 and 9:45AM Eastern Time.

In Table 12 we report the summary statistics for this asset class, including Noise, On-the-run premium, Roll measure (all expressed in basis points) and Turnover (negative) over the April 2005-December 2014 sample, again calculated at the monthly frequency. The correlations among these proxies are intuitively positive, with the exception of Turnover (negative), as reported in Table 13. The reason for this counterintuitive negative correlation is given by the construction of the measure for the Treasuries. As the denominator in the Turnover variable is the total stock of public debt outstanding, the explosion of U.S. sovereign debt as consequence of the automatic stabilizers and the 2009 Fiscal Stimulus appear to severely affect the quality of this measure post 2009, an issue that will become clearer below.

Table 14 presents the estimated breakpoints in the mean at the 5% confidence levels across our four liquidity level measures, employing the Bai and Perron (1998, 2003) preferred approach to the undifferenced and unstandardized Noise, On-the-run premium, Roll measure and Turnover (negative)[37]. The corresponding double maximum tests for the simple breaks in means of the liquidity proxies are reported in Table 15. This table indicates the presence of at least one structural break at the 5% confidence level in all four proxies,

[36] In a speech by Federal Reserve Governor Lael Brainard at Salzburg Global Forum on July 1, 2015, he also mentioned that "since not all broker-dealer inventories are used for market-making activities, the extent to which lower inventories are affecting liquidity is unclear."

[37] Given the small number of time series available for the analysis of liquidity of Treasuries we do not employ dynamic factor model approaches in this Section.

with the exception of the $UD\max$ for the Noise variable. However, for the same variable $WD\max$ reject the null that there is no break. The sequential $\sup F_T(\ell+1|\ell)$ indicates three breakpoints for the Noise and Roll measures, one for the On-the-run premium and four for the Turnover (negative)[38]. Figure 13 reports an informative visualization of when the breakpoints happen over time and in which direction the series breaks. For both the Noise and Roll measures this approach clearly captures the sudden deterioration of market liquidity around the 2008-09 financial crisis and a return to normality mid-2009. The Roll measures seems to suggest further liquidity amelioration in December 2011 (in fact close to the release of the first Proposed Volcker Rule published in 2011M11). The On-the-run premium exhibits qualitatively very similar dynamics, as evident from the North-East panel in Figure 13, but our approach fails to pick up a structural break at the start of the crisis. The only proxy that seems to systematically break in terms of lower liquidity levels for Treasuries is Turnover (negative) in October 2008. However, looking at the components of this measure, this result appears mainly driven by two factors: 1. Treasury issuance dramatically increased after 2008. 2. The Federal Reserve balance sheet structurally increased, holding a very large portfolio of public debt due to the Quantitative Easing. Since the Fed typically is not actively trading, the turnover should intuitively drop.

7 Conclusions

This paper complements, both methodologically and substantively, a rigorous retrospective analysis of post-crisis regulatory intervention in domestic financial markets. Such analysis has been surprisingly bare in terms of systematic empirical evidence and it appears to be a necessary exercise in informing future legislative and rulemaking activities aimed at improving financial markets stability (Cochrane, 2014).

We specifically focus on the aftermath of the 2008-09 U.S. financial crisis and on the role played by the Dodd-Frank Act of 2010 and its corollary Volcker Rule as potential triggers of liquidity shortages driven by retrenchment of financial institutions adversely affected by overreaching regulation.

Several market participants have claimed this assessment to be crucial in the context of an informed cost-benefit analysis of regulatory intervention and rulemaking.

We initially focus on a large set of liquidity proxies with emphasis on the U.S. corporate bond market (an asset class likely to be adversely affected by regulatory tightening through disruption of ordinary market-making activities) and with particular attention paid to different underwriters, credit ratings, and issue sizes.

[38] In Appendix we report the relevant statistics for the $\sup F_T(\ell+1|\ell)$ tests.

Our analysis is based on multiple estimation strategies, including both dynamic factor models and more standard structural breaks and difference-in-differences matching analysis. Reassuringly, the data display no statistical evidence of substantial deterioration in market liquidity after 2010. The tests presented are powerful enough to pick structural breaks in the data -they clearly pinpoint the crisis itself as a liquidity breakpoint- yet they consistently show no significant breaks in the model's factors or in their loadings around the approval of the Dodd-Frank Act, at the time of major banks shutdowns of proprietary trading desks, or at the time of the proposal and finalization of the Volcker Rule.

Evidence from the U.S. Treasuries market, by and large, confirms the absence of big liquidity breaks, in line with our findings on U.S. corporate bonds, calling into question the most negative welfare assessments of the post-crisis regulatory effort, at least along the dimension of market liquidity deterioration.

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Figure 1. Primary Dealer Corporate Bond Holding

This graph shows the time series of the U.S. primary dealer corporate bond holding as the percentage of total corporate bond outstanding (blue line) and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. Primary dealers are a list of banks and non-bank financial firms which serve as trading counterparties of the New York Fed in its implementation of monetary policy. Almost all the major corporate bond underwriters are in the list. The bond holding data is from Federal Reserve Bank of New York, and the amount of outstanding bond is from Securities Industry and Financial Markets Association (SIFMA). The sample period is from January 2002 to December 2014. The data frequency is monthly. The grey area indicates recession.

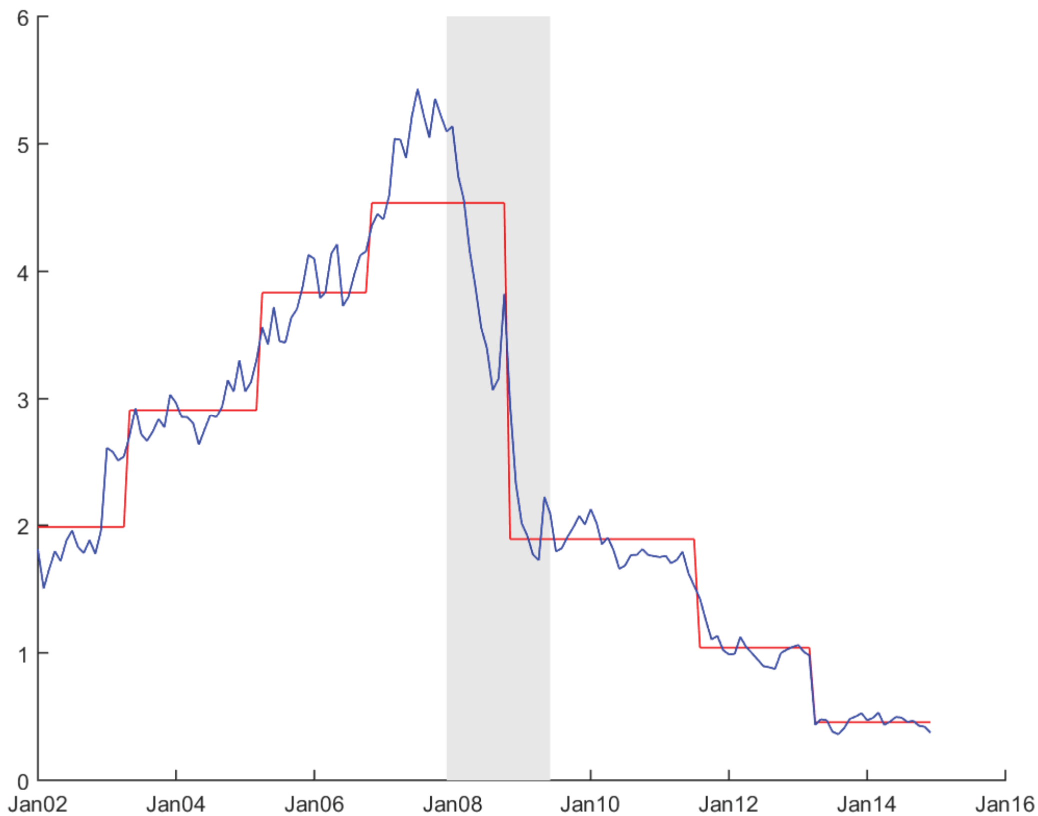


Figure 2. Timeline of Crisis and Post-Crisis Regulatory Activity

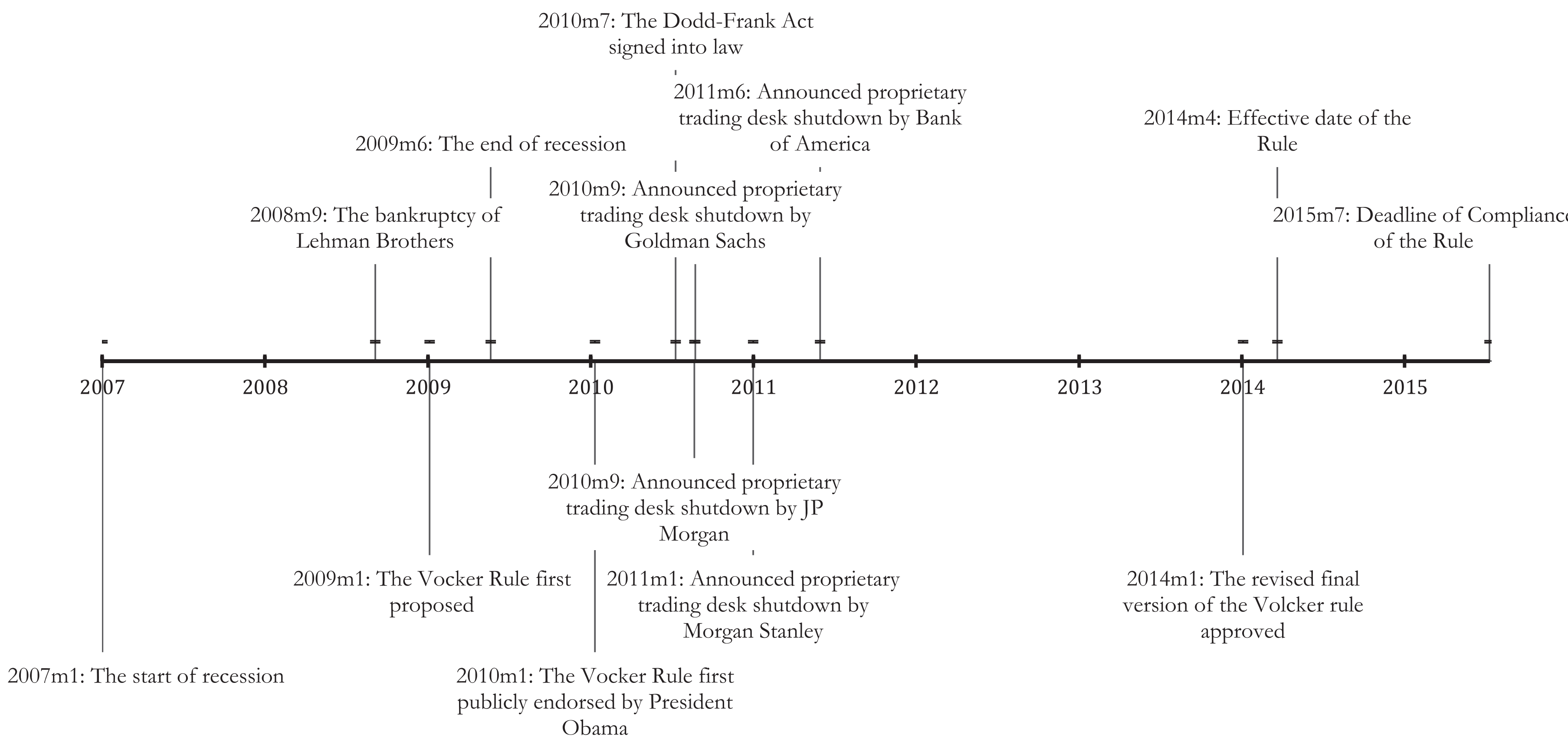
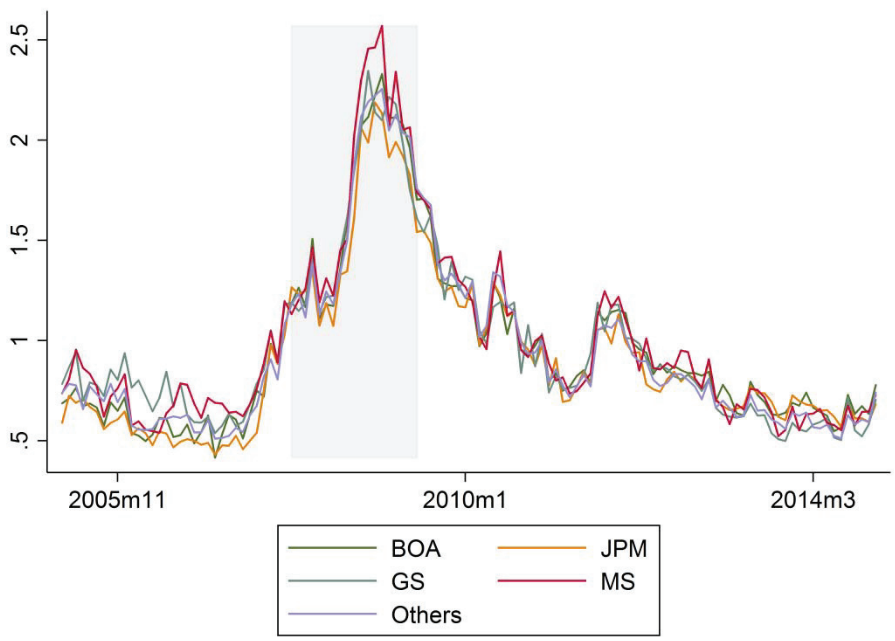


Figure 3. Time Series of Liquidity Measures (Underwriter-Level)

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.

Amihud



Amihud (sd)

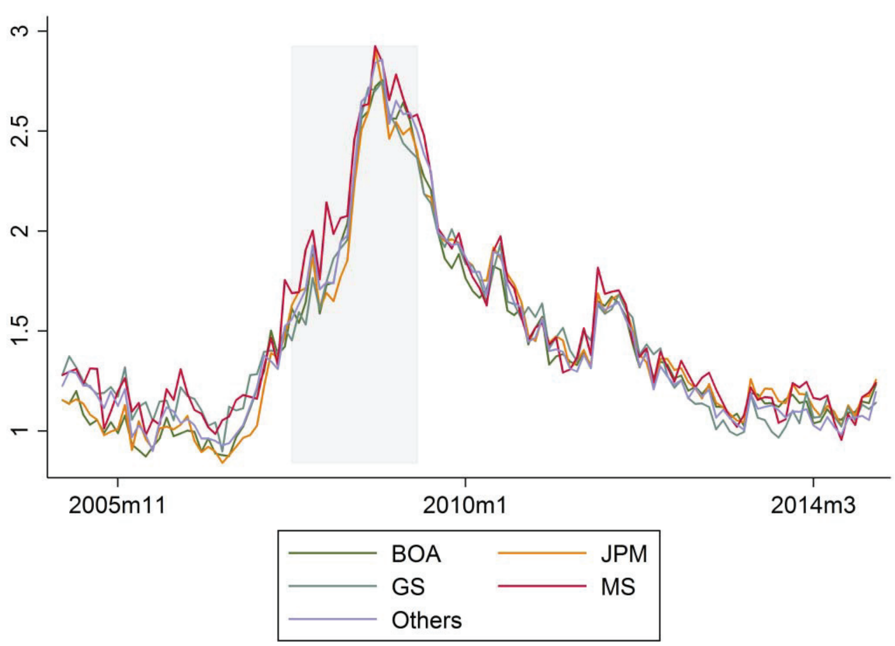
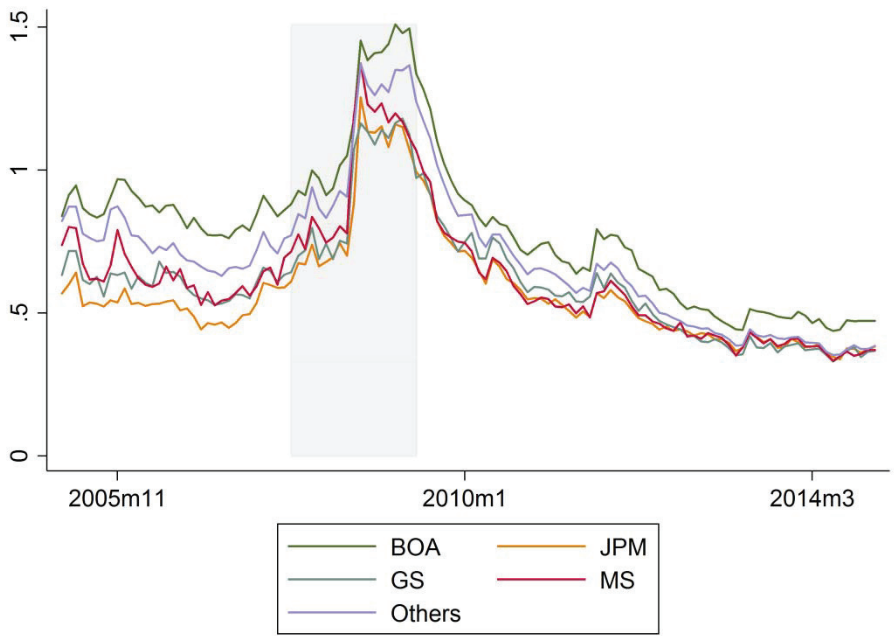


Figure 3 (continued). Time Series of Liquidity Measures (Underwriter-Level)

IRC



IRC (sd)

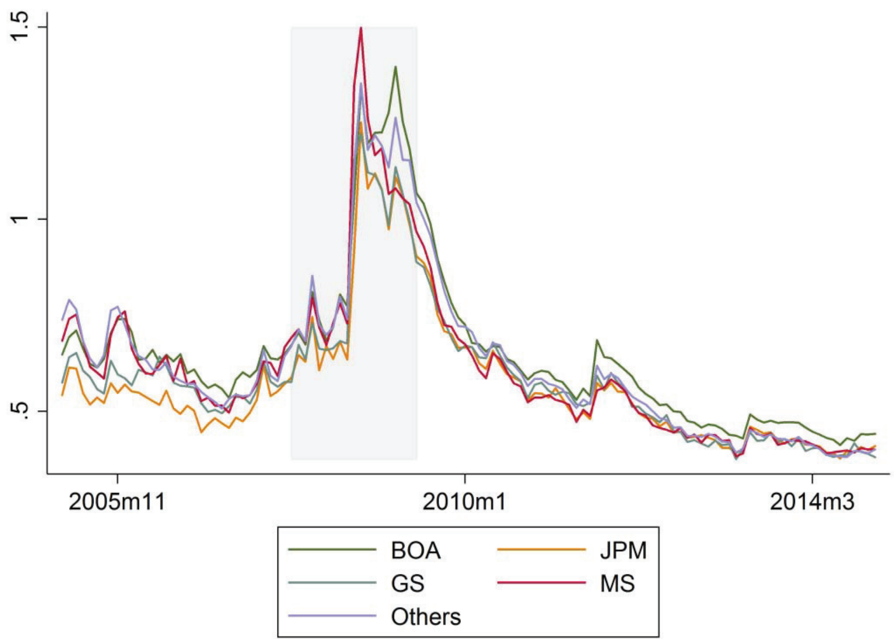
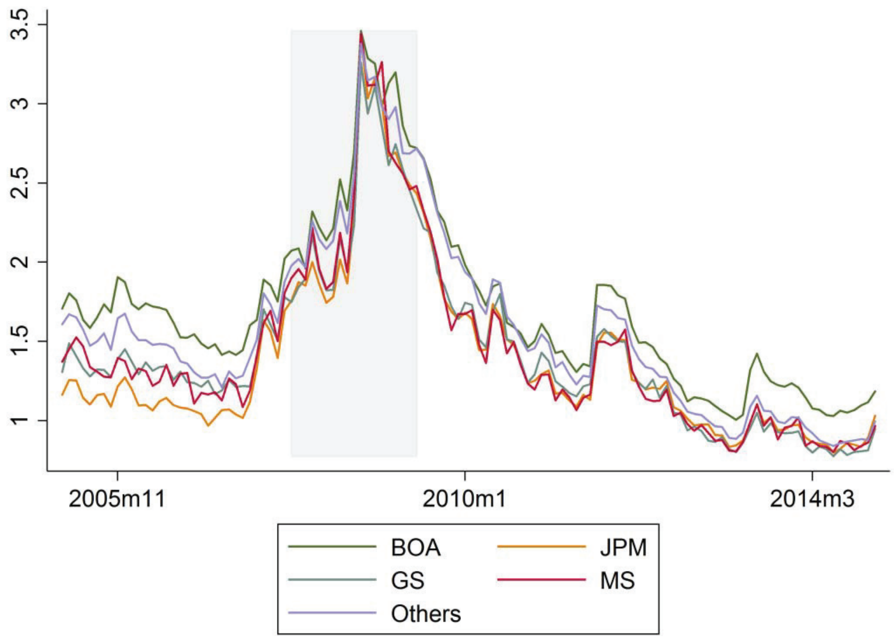


Figure 3 (continued). Time Series of Liquidity Measures (Underwriter-Level)

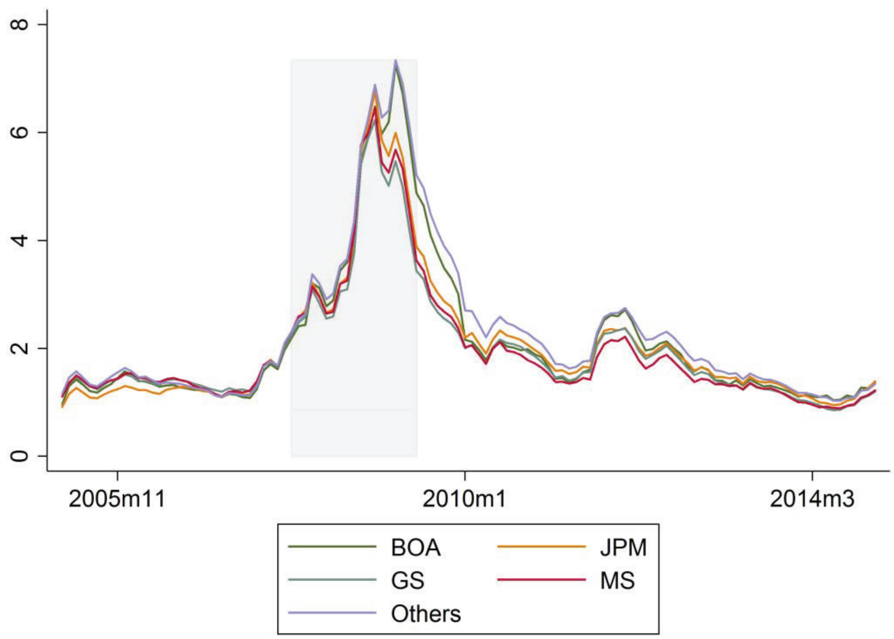
Roll



Non-block Trade

Figure 3 (continued). Time Series of Liquidity Measures (Underwriter-Level)

Spread



Turnover (negative)

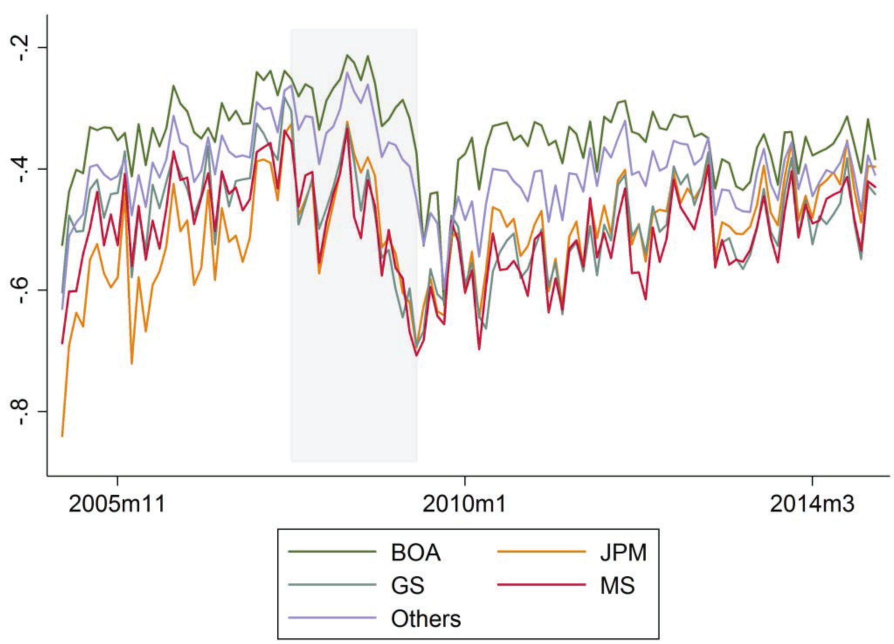


Figure 3 (continued). Time Series of Liquidity Measures (Underwriter-Level)

Zero-trading Days

Figure 4. Time Series of Liquidity (Aggregate-level)

This graph shows the time series of 9 aggregate-level liquidity measures of U.S. corporate bond market (blue line), and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

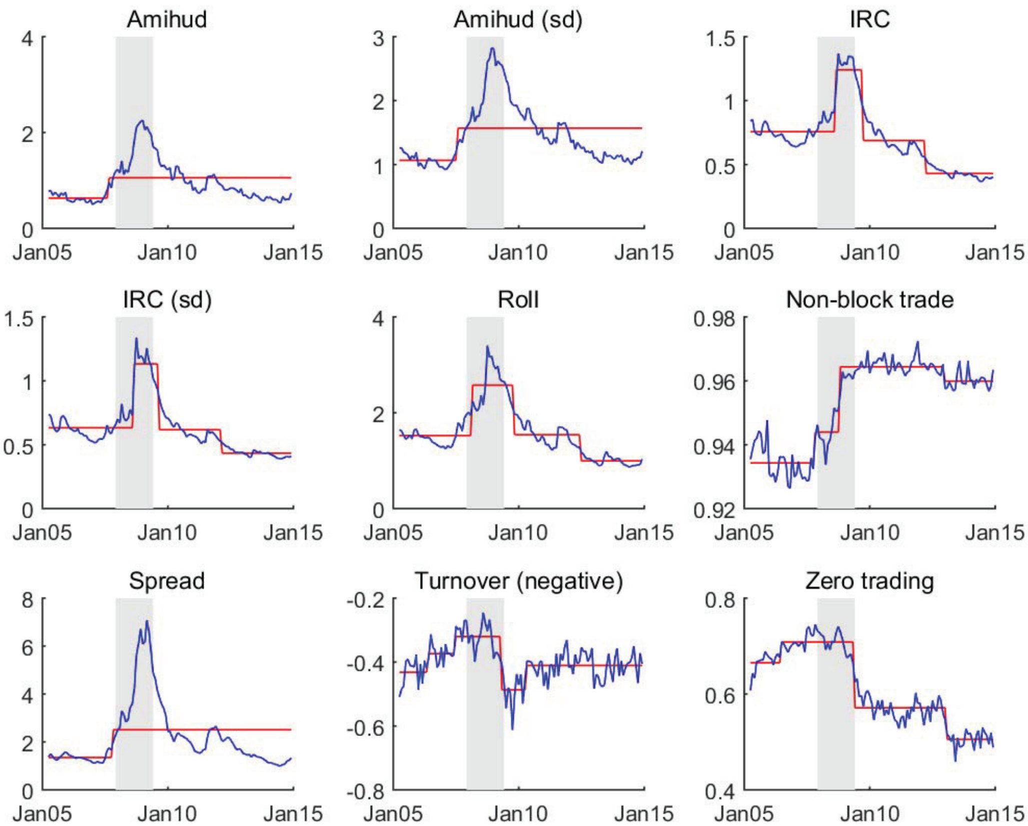


Figure 5. Frequency of Break Dates of Mean Liquidity (Underwriter-level)

This graph shows the frequency of break dates in means of 180 underwriter-level liquidity measures for the U.S. corporate bond market. The x-axis shows the break date and the y-axis shows the corresponding fraction of the 180 liquidity measures which have a break at this break date. The break dates are estimated using the Bai and Perron (1998, 2003) approach with 5% significance level. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. The sample period is from April 2005 to December 2014. The data frequency is monthly. We run the test iteratively for each measure, and the following figure shows the frequency across all the 180 measures. The grey area indicates recession.

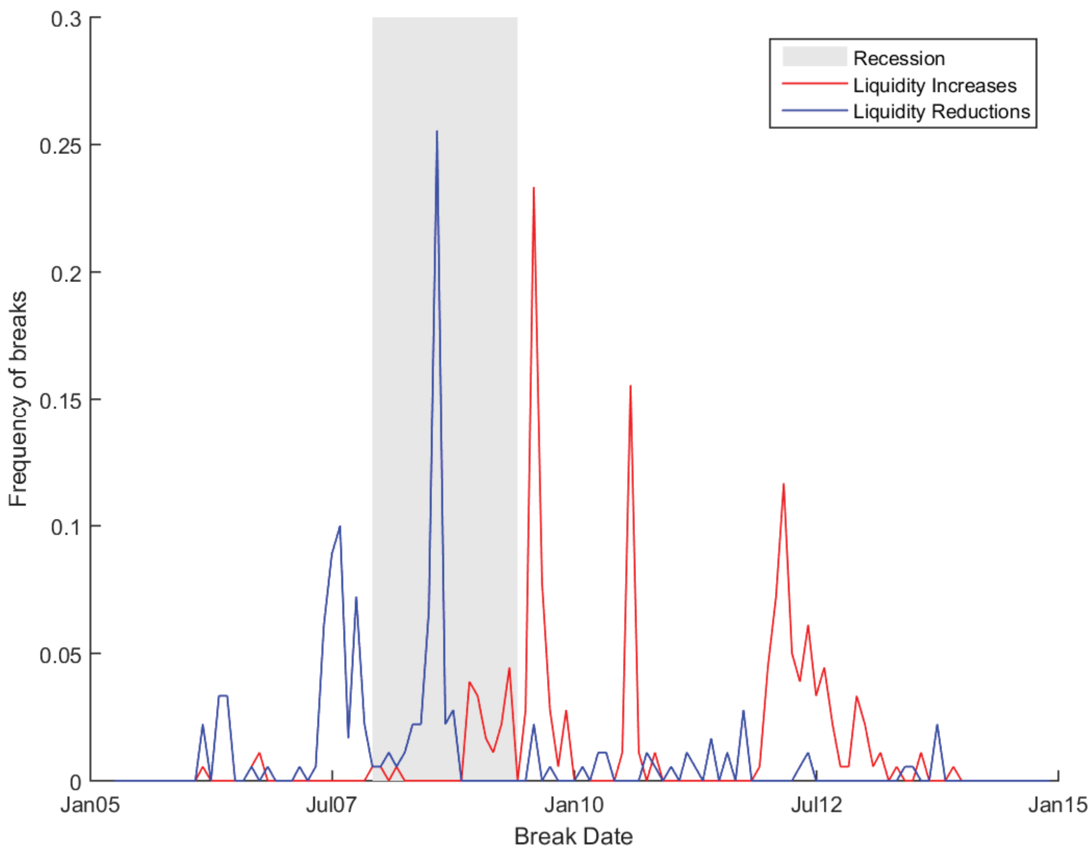


Figure 6. Decomposition of Break Dates by Underwriter (Underwriter-level)

This graph shows the decomposition of break dates by underwriter. The x-axis shows the break date and the y-axis shows the corresponding fraction of the 36 (=9×2×2) liquidity measures of each underwriter which have a break at this break date. The break dates are estimated using the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

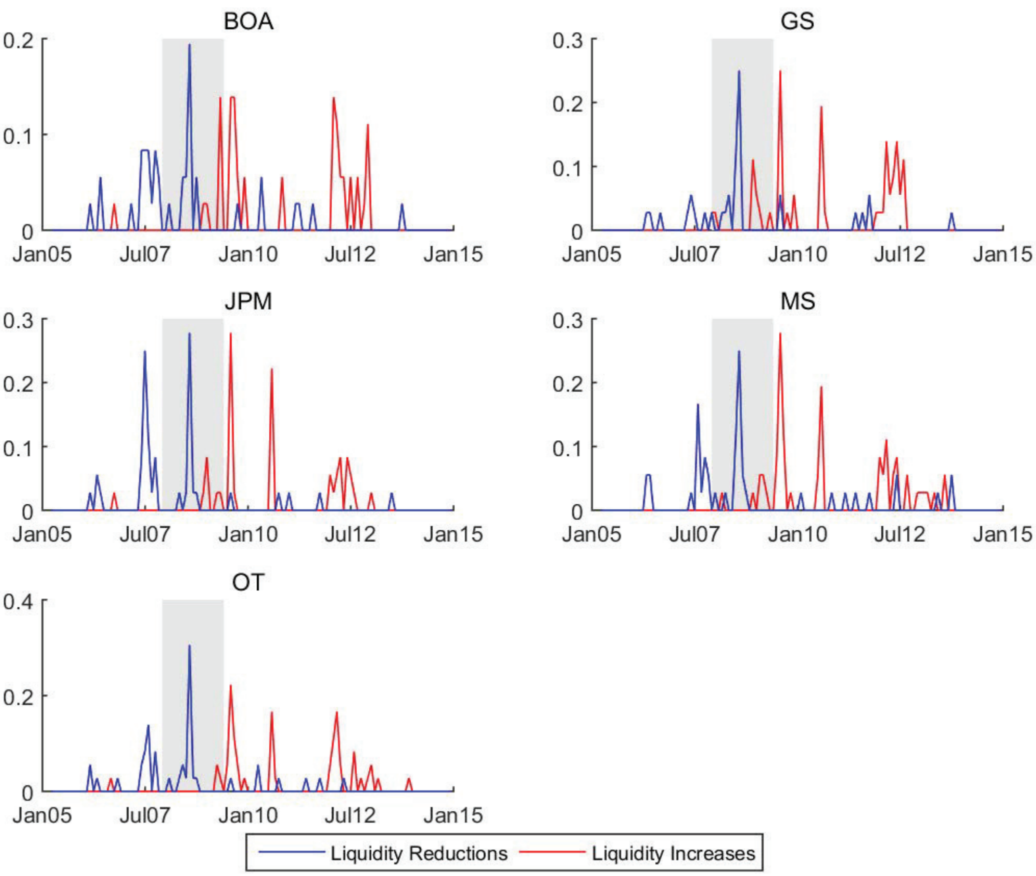


Figure 7. Decomposition of Break Dates by Bond Type (Underwriter-level)

This graph shows the decomposition of break dates by bond types. The x-axis shows the break date 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 break date. The break dates are estimated using the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

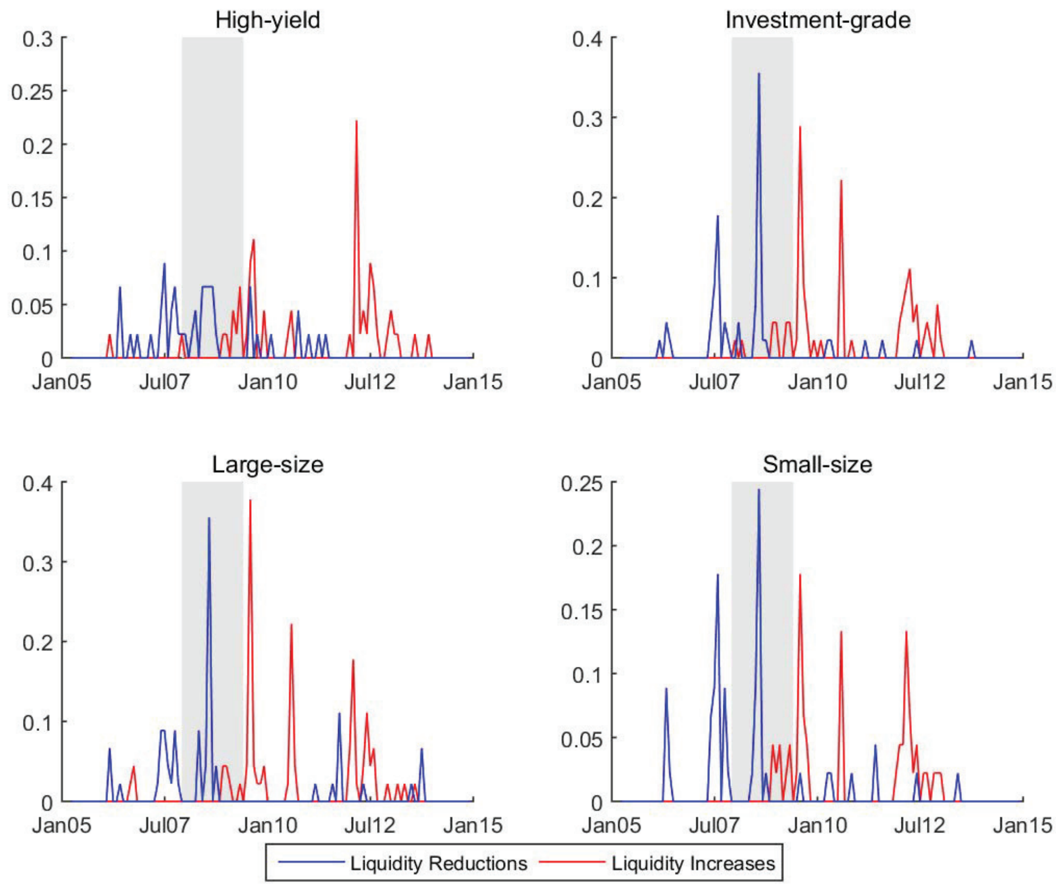


Figure 8. Decomposition of Break Dates by Measure (Underwriter-level)

This graph shows the decomposition of break dates by bond types. The x-axis shows the break date 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 break date. The break dates are estimated using the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

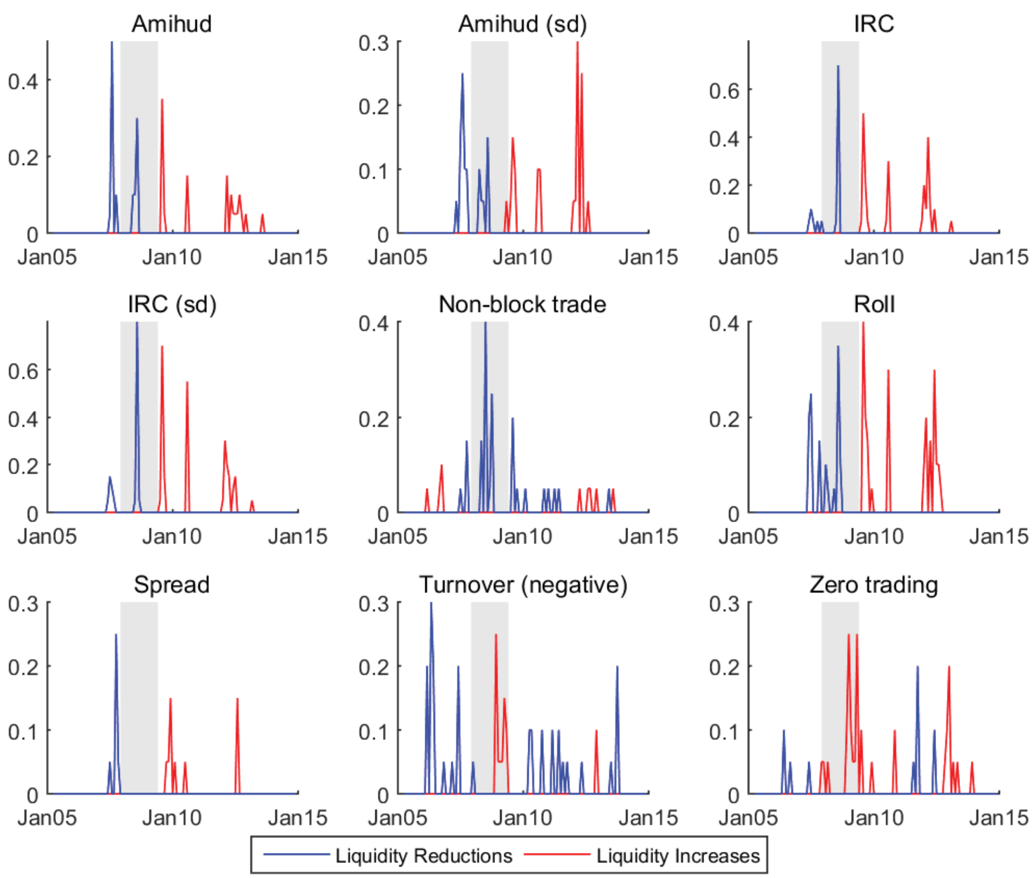


Figure 9. Test Statistics of Breaks on the Liquidity Factor Structure: Single Break Test

This graph shows the test statistics of a single break in factor structure of 180 underwriter-level liquidity measures employing the Chen et al. (2014) approach. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. The sample period is from April 2005 to December 2014. The full interval over which the unknown breakpoint is allowed to belong is from February 2008 to December 2011. The liquidity measures are differenced and standardized. The data frequency is monthly. The grey area indicates recession. The critical values are obtained from Chen et al. (2014).

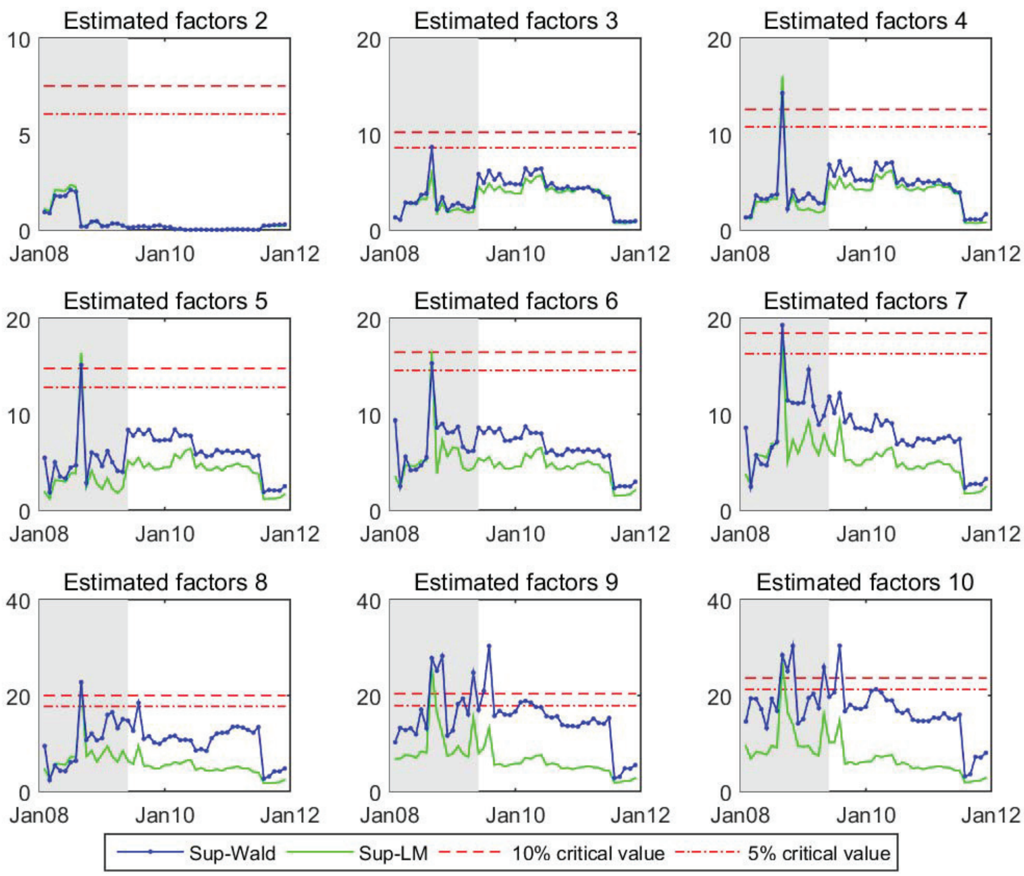


Figure 10. Liquidity of Volcker Rule and Non-Volcker Rule Bonds (Matched Sample)

This graph shows the time series of liquidity of Volcker Rule bonds and non-Volcker Rule bonds around the time when revised finalized version of the Volcker Rule is approved (January 2014). A non-Volcker Rule bond is defined as a bond which at least one of the underwriters is not subject to the Volcker Rule. A Volcker Rule bond is defined as a bond which all of the underwriters are subject to the Volcker Rule. Each of the non-Volcker Rule bonds in our sample is matched to a Volcker Rule bond which is issued at the same month, matures in the same year, has the same rating (investment-grade/high-yield), and has a relative size difference less than 50% of the average size of the pair. If there are more than one bond satisfies the above criteria, we keep the one with smallest relative size difference. Both time series are normalized to 0 in December 2013. The red vertical line indicates the date when the revised finalized version of the Volcker Rule was approved (2014m1). The sample period is from January 2013 to December 2014. The data frequency is monthly.

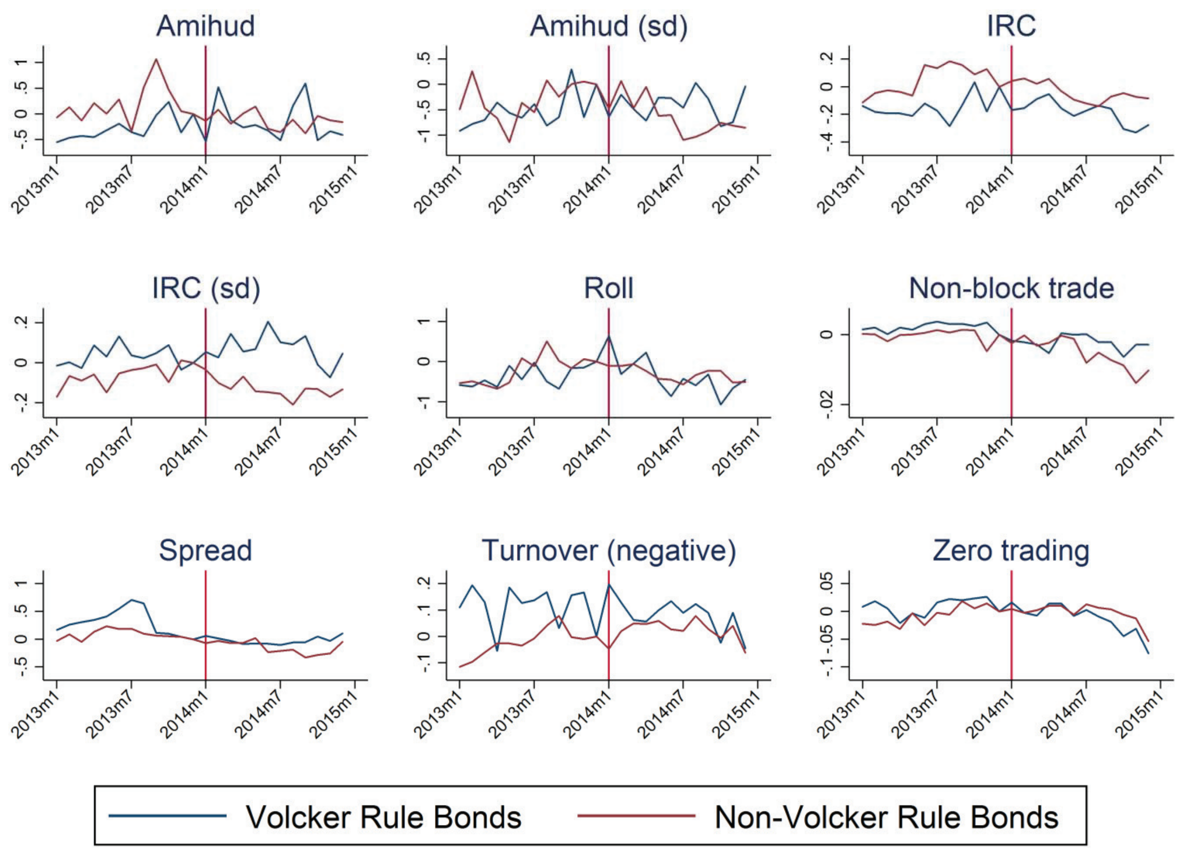


Figure 11. Liquidity Difference between Volcker Rule and Non-Volcker Rule Bonds

This graph shows the time series of liquidity difference between of bonds underwritten by Volcker Rule underwriters and non-Volcker Rule underwriters (blue line), and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

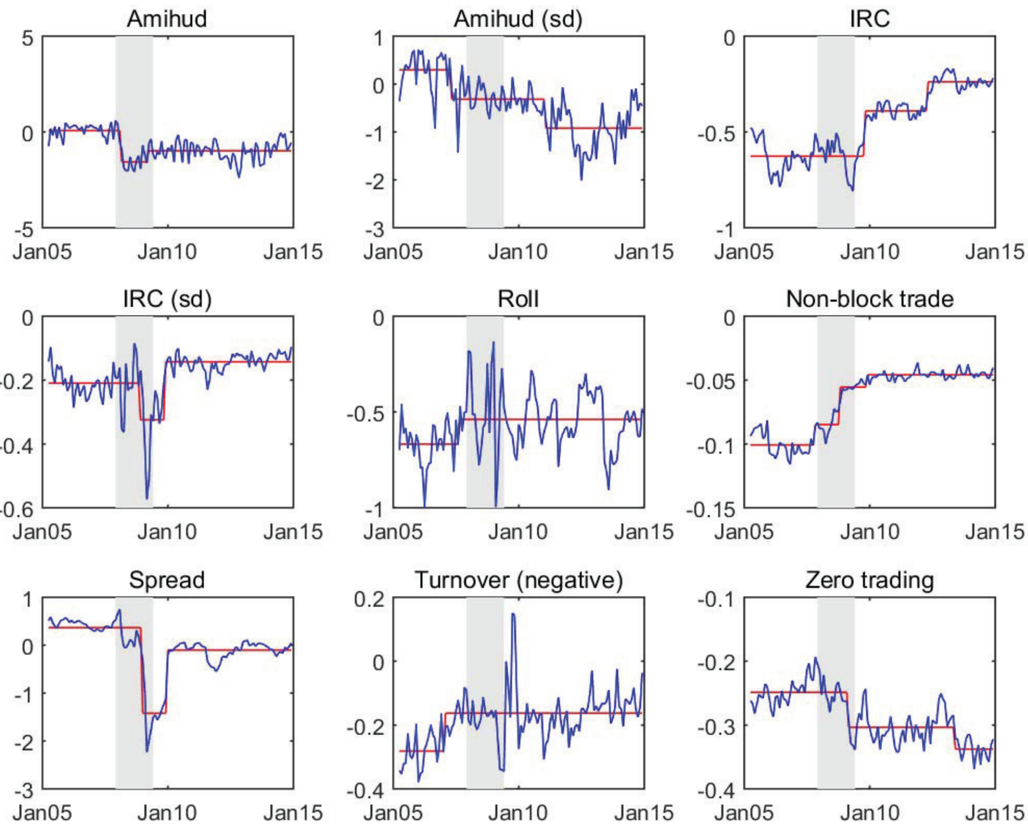


Figure 12. Liquidity Difference between Lehman Brothers and Other Underwriters

This graph shows the time series of liquidity difference between of bonds underwritten by Lehman Brothers and all the other underwriters (blue line), and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The liquidity measures are constructed using bonds issued before September 2008. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

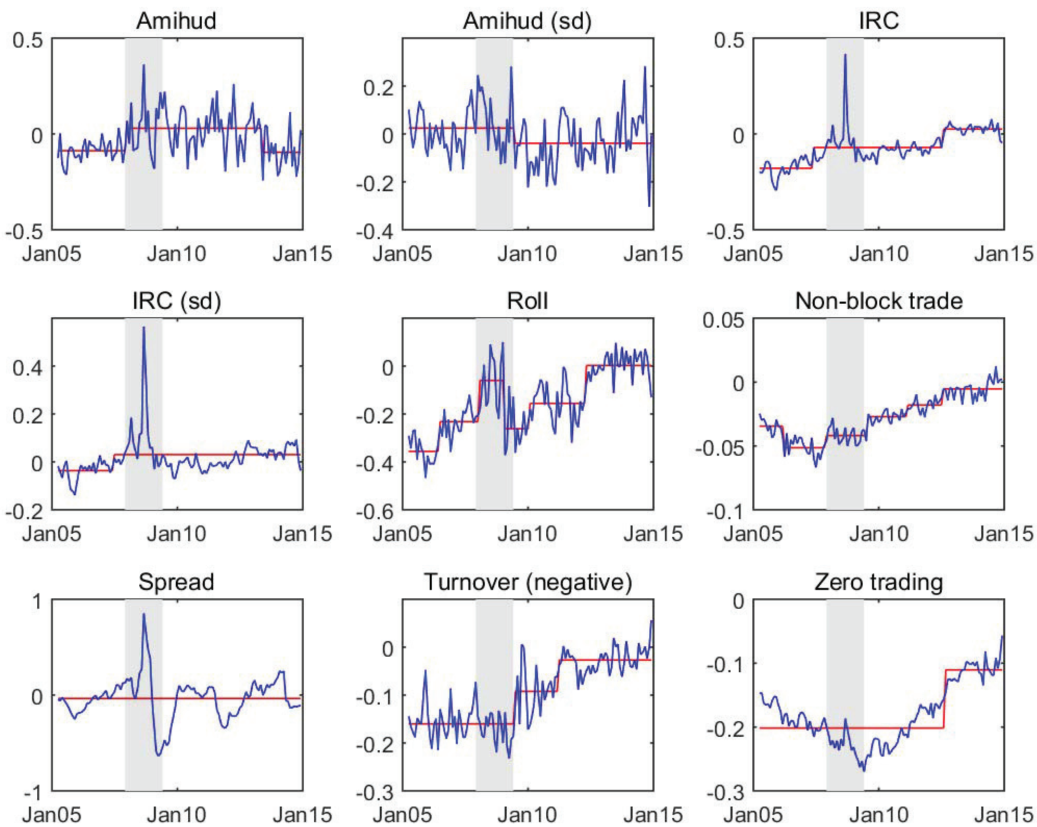
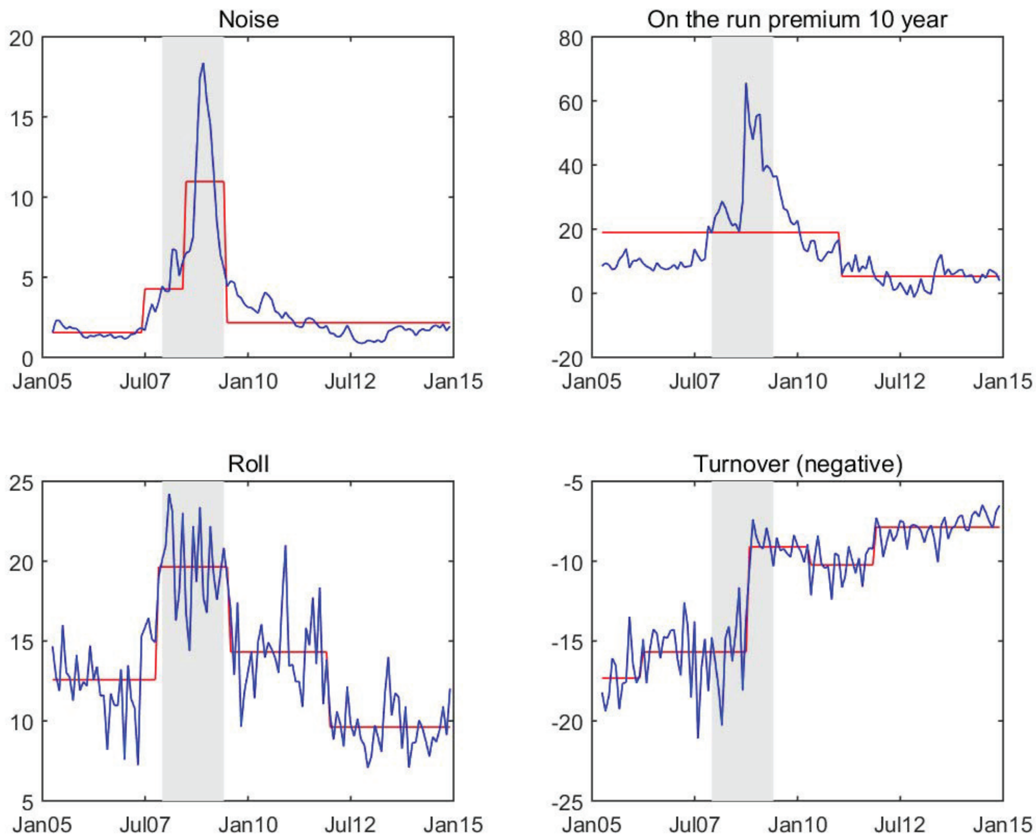


Figure 13. Time Series of Liquidity of the U.S. Treasury Liquidity

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 line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.



Appendix Figure 1. Liquidity Difference between Bear Stearns and Other Underwriters

This graph shows the time series of liquidity difference between bonds underwritten by Bear Stearns and all the other underwriters (blue line), and the estimated mean for each sub-period (red line). The break dates are estimated by the Bai and Perron (1998, 2003) approach with 5% significance level. The liquidity measures are constructed using bonds issued before March 2008. The sample period is from April 2005 to December 2014. The data frequency is monthly. The grey area indicates recession.

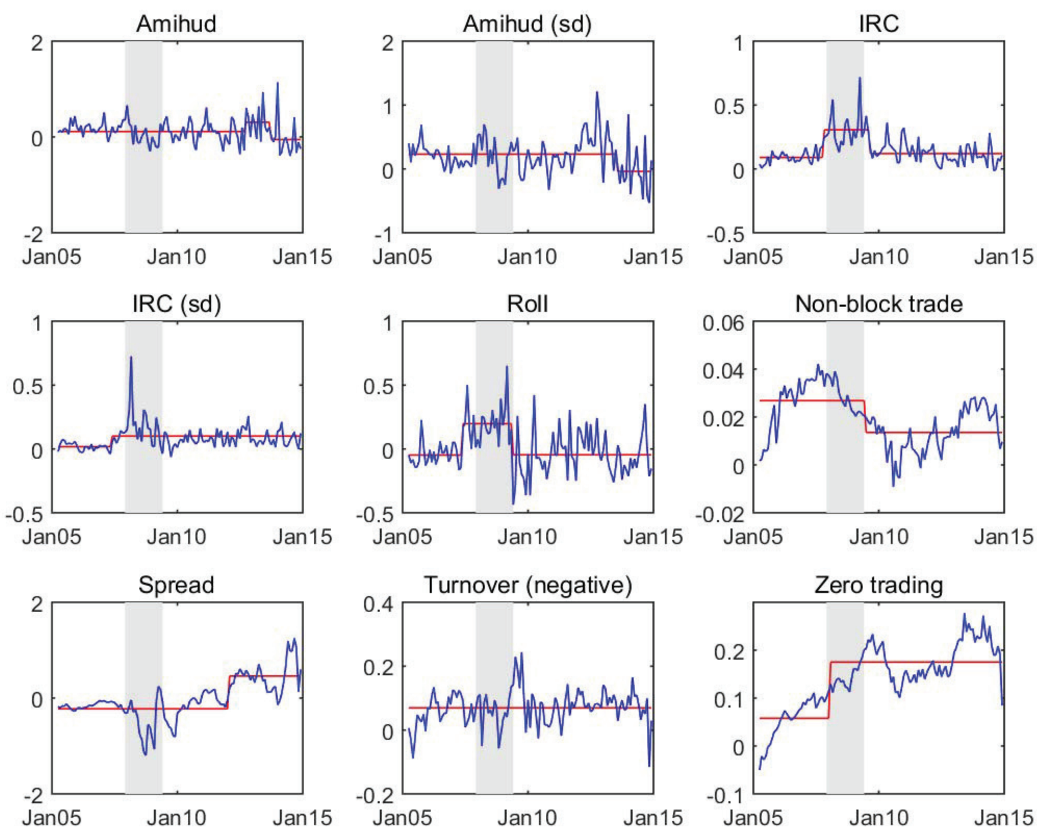


Table 1: Summary Statistics of the U.S. Corporate Bond Liquidity (Aggregate Level)

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), Roll and Spread is percentage point. The unit of Non-block trade, Turnover (negative)and Zero-trading is 1.

Measures	N	mean	sd	p10	p25	p50	p75	p90
Amihud	117	0.95	0.43	0.57	0.63	0.79	1.14	1.63
Amihud (sd)	117	1.45	0.47	1.03	1.10	1.28	1.67	2.25
IRC	117	0.70	0.25	0.41	0.49	0.68	0.82	1.10
IRC (sd)	117	0.62	0.21	0.42	0.46	0.59	0.69	0.94
Roll	117	1.57	0.56	0.93	1.19	1.47	1.83	2.43
Non-block trade	117	0.95	0.01	0.93	0.94	0.96	0.96	0.97
Spread	117	2.20	1.37	1.14	1.33	1.67	2.44	4.15
Turnover (negative)	117	-0.40	0.06	-0.48	-0.44	-0.40	-0.37	-0.32
Zero-trading	117	0.61	0.08	0.51	0.55	0.59	0.69	0.72

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

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.

	Amihud	Amihud (sd)	IRC	IRC (sd)	Roll	Non-block trade	Spread	Turnover (negative)
Amihud (sd)	0.99							
IRC	0.85	0.84						
IRC (sd)	0.90	0.88	0.98					
Roll	0.92	0.91	0.97	0.97				
Non-block trade	0.31	0.36	-0.13	-0.03	-0.01			
Spread	0.97	0.95	0.86	0.91	0.91	0.28		
Turnover (negative)	0.18	0.11	0.14	0.13	0.21	-0.27	0.13	
Zero-trading	0.33	0.28	0.66	0.57	0.59	-0.72	0.33	0.53

Table 3. Sample Mean and Standard Deviation of Liquidity (Underwriter Level)

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 (BOA), Goldman Sachs (GS), JP Morgan (JPM), Morgan Stanley (MS), and all the other underwriters (OT). Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. The sample period is from April 2005 to December 2014. The data frequency is monthly. The unit of Amihud, Amihud (sd), IRC, IRC (sd), Roll and Spread 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	Spread	Turnover (negative)	Zero-trading
BOA	High-yield	0.70	1.14	0.54	0.56	1.32	0.70	4.46	-0.48	0.49
		(0.26)	(0.29)	(0.17)	(0.19)	(0.42)	(0.08)	(2.15)	(0.1)	(0.07)
BOA	Investment-grade	0.99	1.47	0.81	0.66	1.73	0.98	2.04	-0.34	0.70
		(0.46)	(0.5)	(0.27)	(0.22)	(0.56)	(0.01)	(1.35)	(0.06)	(0.07)
BOA	Large-size	0.91	1.54	0.70	0.71	1.28	0.93	2.13	-0.68	0.14
		(0.51)	(0.55)	(0.33)	(0.3)	(0.6)	(0.02)	(1.33)	(0.17)	(0.04)
BOA	Small-size	0.97	1.41	0.80	0.65	1.74	0.97	2.14	-0.33	0.72
		(0.42)	(0.46)	(0.26)	(0.21)	(0.55)	(0.01)	(1.38)	(0.06)	(0.06)
GS	High-yield	0.78	1.25	0.62	0.60	1.52	0.74	4.68	-0.47	0.50
		(0.3)	(0.42)	(0.18)	(0.18)	(0.5)	(0.07)	(1.97)	(0.11)	(0.12)
GS	Investment-grade	0.99	1.48	0.61	0.59	1.43	0.95	1.69	-0.49	0.47
		(0.44)	(0.46)	(0.21)	(0.19)	(0.54)	(0.02)	(1.02)	(0.08)	(0.09)
GS	Large-size	0.89	1.54	0.73	0.73	1.26	0.94	1.75	-0.79	0.11
		(0.59)	(0.56)	(0.37)	(0.31)	(0.58)	(0.02)	(1.02)	(0.16)	(0.05)
GS	Small-size	0.98	1.46	0.59	0.56	1.47	0.93	2.00	-0.44	0.52
		(0.39)	(0.43)	(0.18)	(0.16)	(0.52)	(0.03)	(1.11)	(0.07)	(0.08)

Table 3 (continued). Sample Mean of Liquidity (Underwriter Level)

Bank	Bond Type	Amihud	Amihud (sd)	IRC	IRC (sd)	Roll	Non-block trade	Spread	Turnover (negative)	Zero-trading
JPM	High-yield	0.70	1.14	0.54	0.56	1.32	0.70	4.46	-0.48	0.49
		(0.26)	(0.29)	(0.17)	(0.19)	(0.42)	(0.08)	(2.15)	(0.1)	(0.07)
JPM	Investment-grade	0.99	1.47	0.81	0.66	1.73	0.98	2.04	-0.34	0.70
		(0.46)	(0.5)	(0.27)	(0.22)	(0.56)	(0.01)	(1.35)	(0.06)	(0.07)
JPM	Large-size	0.91	1.54	0.70	0.71	1.28	0.93	2.13	-0.68	0.14
		(0.51)	(0.55)	(0.33)	(0.3)	(0.6)	(0.02)	(1.33)	(0.17)	(0.04)
JPM	Small-size	0.97	1.41	0.80	0.65	1.74	0.97	2.14	-0.33	0.72
		(0.42)	(0.46)	(0.26)	(0.21)	(0.55)	(0.01)	(1.38)	(0.06)	(0.06)
MS	High-yield	0.78	1.25	0.62	0.60	1.52	0.74	4.68	-0.47	0.50
		(0.3)	(0.42)	(0.18)	(0.18)	(0.5)	(0.07)	(1.97)	(0.11)	(0.12)
MS	Investment-grade	0.99	1.48	0.61	0.59	1.43	0.95	1.69	-0.49	0.47
		(0.44)	(0.46)	(0.21)	(0.19)	(0.54)	(0.02)	(1.02)	(0.08)	(0.09)
MS	Large-size	0.89	1.54	0.73	0.73	1.26	0.94	1.75	-0.79	0.11
		(0.59)	(0.56)	(0.37)	(0.31)	(0.58)	(0.02)	(1.02)	(0.16)	(0.05)
MS	Small-size	0.98	1.46	0.59	0.56	1.47	0.93	2.00	-0.44	0.52
		(0.39)	(0.43)	(0.18)	(0.16)	(0.52)	(0.03)	(1.11)	(0.07)	(0.08)
OT	High-yield	0.74	1.24	0.59	0.60	1.43	0.72	4.64	-0.49	0.52
		(0.25)	(0.3)	(0.18)	(0.17)	(0.41)	(0.07)	(2.17)	(0.1)	(0.07)
OT	Investment-grade	0.98	1.48	0.71	0.63	1.59	0.97	2.12	-0.39	0.63
		(0.47)	(0.51)	(0.26)	(0.22)	(0.59)	(0.01)	(1.4)	(0.06)	(0.08)
OT	Large-size	0.75	1.38	0.63	0.65	1.18	0.92	1.92	-0.69	0.12
		(0.46)	(0.5)	(0.31)	(0.27)	(0.57)	(0.02)	(1.14)	(0.14)	(0.05)
OT	Small-size	0.98	1.46	0.71	0.63	1.62	0.96	2.33	-0.38	0.66
		(0.44)	(0.48)	(0.25)	(0.21)	(0.57)	(0.01)	(1.45)	(0.06)	(0.07)

Table 4. Break Dates in the Means of Liquidity (Aggregate-level)

This table lists break dates in the means 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% significance level. The sample period is from April 2005 to December 2014. The data frequency is monthly.

Measures	Break Dates			
Amihud	2007m8			
Amihud (sd)	2007m7			
IRC	2008m8	2009m9	2012m3	
IRC (sd)	2008m8	2009m8	2012m2	
Roll	2008m2	2009m10	2012m6	
Non-block trade	2007m10	2008m10	2012m12	
Spread	2007m10			
Turnover (negative)	2006m5	2007m6	2009m4	2010m4
Zero trading	2006m6	2009m5	2013m1	

Table 5. Double Maximum Test Statistics of Breaks in the Means of Liquidity (Aggregate-level)

This table lists the Dmax statistics of break dates in the means 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% 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).

Measures	WDmax	5% critical value of WDmax	UDmax	5% critical value of UDmax
Amihud	70.42	10.39	41.56	9.52
Amihud (sd)	62.73	10.39	37.02	9.52
IRC	118.75	10.39	78.69	9.52
IRC (sd)	65.80	10.39	49.45	9.52
Roll	62.63	10.39	36.96	9.52
Non-block trade	370.07	10.39	245.22	9.52
Spread	14.19	10.39	8.38	9.52
Turnover (negative)	34.08	10.39	29.66	9.52
Zero trading	397.48	10.39	298.77	9.52

Table 6. Number of Dynamic Factors (Underwriter-level)

This graph shows the estimated number of factors in 180 underwriter-level liquidity measures for the U.S. corporate bond market. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. 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.

Method	Number of Estimated Factors
Ahn & Horenstein (2013) ER	1
Ahn & Horenstein (2013) GR	1
Bai & Ng (2002) IC1	10
Bai & Ng (2002) IC2	7
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

Table 7. Number of Factors Before and After Break: Single Break Test (Underwriter-level)

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 (ER) 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.

Number of Factors:			
Whole Sample	Before Break	After Break	Break Dates
2	1	1	2008m7
3	2	1	2008m9
4	2	1	2008m9
5	2	1	2008m9
6	2	1	2008m9
7	2	1	2008m9
8	2	1	2008m9
9	1	3	2009m8
10	1	3	2009m8

Table 8: Break Dates of Liquidity Factor Structure (Underwriter-level)

This table shows the break dates in factor structure of the U.S. corporate bond market liquidity employing the Bai and Perron (1998, 2003) approach with 5% significance level. Liquidity measures are in underwriter-level. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. 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. The following table shows the break dates estimated in each test.

Number of factors	Break Dates				
2	None				
3	2008m8	2009m8			
4	2008m9				
5	2008m9				
6	2008m8	2009m8			
7	2008m9				
8	2007m9	2008m9	2009m9	2010m9	2011m10
9	2007m9	2008m9	2009m11		
10	2006m3	2007m9	2008m9	2009m9	2010m9

Table 9: Double Maximum Test Statistics of Breaks in the Liquidity Factor Structure

(Underwriter-level)

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% significance level. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. 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).

Number of factors	WDmax	5% critical value of WDmax	UDmax	5% critical value of UDmax
2	4.17	10.39	3.26	9.52
3	20.59	13.66	17.63	12.59
4	181.24	16.07	129.73	14.85
5	164.98	18.38	111.14	17.00
6	3604.73	20.30	2508.65	18.91
7	57642.80	22.55	40677.60	21.01
8	1.18E+13	24.34	8.42E+12	22.80
9	1.27E+05	26.10	9.78E+04	24.56
10	5.52E+15	27.99	4.04E+15	26.48

Table 10. Number of Factors of Each Subperiod: Multiple Break Test (Underwriter-level)

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% significance level, and the number of factors of each subperiod is estimated using the eigenvalue ratio (ER) 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.

Number of Factors						
Whole Sample	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 4	Subperiod 5	Subperiod 6
2	NA					
3	1	1	3			
4	2	1				
5	2	1				
6	1	1	3			
7	2	1				
8	3	1	1	1	2	2
9	3	1	1	3		
10	1	3	1	1	1	3

Table 11. Difference-in-Difference Regression

This table shows the difference-in-difference regression of Volcker Rule bonds and non-Volcker Rule bonds around the time when revised finalized version of the Volcker Rule is approved (January 2014). A non-Volcker Rule bond is defined as a bond which at least one of the underwriters is not subject to the Volcker Rule. Each of the non-Volcker Rule bonds in our sample is matched to a Volcker Rule bond which is issued at the same month, matures in the same year, has the same rating (investment-grade/high-yield), and has a relative size difference less than 50% of the average size of the pair. The sample period is from January 2013 to December 2014. The data frequency is monthly. The standard errors are two-way clustered at the bond and month level.

	(1) Amihud	(2) Amihud (sd)	(3) IRC	(4) IRC (sd)	(5) Roll	(6) Non-block trade	(7) Spread	(8) Turnover (negative)	(9) Zero-trading
Volcker Bond*Post Volcker	0.211	0.363	0.101	0.0987**	0.0976	0.000547	0.125	0.00304	0.00120
	[0.145]	[0.283]	[0.0615]	[0.0380]	[0.165]	[0.000642]	[0.0833]	[0.0418]	[0.00639]
1/Issue Age	-8.076***	-6.296**	-0.0927	-0.00775	-5.866***	-0.0148	1.822**	1.762*	0.567***
	[2.513]	[2.910]	[0.588]	[0.495]	[1.939]	[0.0151]	[0.867]	[0.883]	[0.133]
1/(Issue Age)^2	13.20**	8.890*	-0.265	-0.0589	6.384*	-0.0131	-2.736**	-6.032***	-1.269***
	[5.159]	[4.903]	[0.965]	[0.742]	[3.192]	[0.0295]	[1.323]	[1.703]	[0.232]
Time F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1011	1011	2969	1533	3401	9380	9347	9380	9380
Adjusted R-squared	0.200	0.322	0.335	0.463	0.275	0.582	0.695	0.229	0.845

Standard errors in brackets
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 12. Summary Statistics of the U.S. Treasury Liquidity

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.

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

Table 13. Correlation Table of the U.S. Treasury Liquidity

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.

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

Table 14: Break Dates of the U.S. Treasury Liquidity

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

Measure	Break Dates			
Noise	2007m6	2008m6	2009m6	
On the run premium	2011m1			
Roll	2007m10	2009m7	2011m12	
Turnover (negative)	2006m3	2008m10	2010m4	2011m11

Table 15: Double Maximum Test Statistics of Multiple Breaks in the Means of the U.S. Treasury Liquidity

This table lists the double maximum statistics of break dates in the means of liquidity measures of U.S. Treasury market. The dates are estimated by the Bai and Perron (1998, 2003) approach with 5% 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).

Measure	WDmax	5% critical value of WDmax	UDmax	5% 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

Appendix Table 1: Sequential Test Statistics of Multiple Breaks in the Means of Liquidity (Aggregate-level)

This table lists the sequential test statistics of break dates in the means 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% 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).

Measure	$F_T(2\|1)$	5% critical value of $F_T(2\|1)$	$F_T(3\|2)$	5% critical value of $F_T(3\|2)$	$F_T(4\|3)$	5% critical value of $F_T(4\|3)$	$F_T(5\|4)$	5% critical value of $F_T(5\|4)$
Amihud	4.77	9.10						
Amihud (sd)	4.20	9.10						
IRC	38.60	9.10	24.08	10.55	6.13	11.36		
IRC (sd)	45.50	9.10	35.85	10.55	7.17	11.36		
Roll	15.55	9.10	21.60	10.55	3.60	11.36		
Non-block trade	9.44	9.10	28.85	10.55	9.15	11.36		
Spread	2.15	9.10						
Turnover (negative)	20.29	9.10	20.31	10.55	20.31	11.36	2.12	12.35
Zero trading	124.21	9.10	15.45	10.55	6.65	11.36		

Appendix Table 2: Sequential Test Statistics of Multiple Breaks in the Liquidity Factor Structure (Underwriter-level)

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% significance level. Each underwriter has four liquidity measures: large issue size, small issue size, investment-grade, and high-yield. 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).

Number of factors	$F_T(2\|1)$	5% critical value of $F_T(2\|1)$	$F_T(3\|2)$	5% critical value of $F_T(3\|2)$	$F_T(4\|3)$	5% critical value of $F_T(4\|3)$	$F_T(5\|4)$	5% critical value of $F_T(5\|4)$
2								
3	19.07	12.25	4.91	13.83				
4	14.35	14.60						
5	14.88	16.76						
6	32.27	18.68	19.72	20.57				
7	20.21	20.76						
8	185.50	22.62	185.50	24.64	85.77	25.57	50.42	26.54
9	46.89	24.34	46.89	26.42	22.85	27.66		
10	3265.60	26.20	538.61	28.23	590.41	29.44	590.41	30.31

Appendix Table 3: Sequential Test Statistics of Multiple Breaks in the Means of the U.S. Treasury Liquidity

This table lists the double maximum statistics of break dates in the means of liquidity measures of U.S. Treasury market. The dates are estimated by the Bai and Perron (1998, 2003) approach with 5% 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).

Measure	$F_T(2\|1)$	5% critical value of $F_T(2\|1)$	$F_T(3\|2)$	5% critical value of $F_T(3\|2)$	$F_T(4\|3)$	5% critical value of $F_T(4\|3)$	$F_T(5\|4)$	5% critical value of $F_T(5\|4)$
Noise	10.56	9.10	21.63	10.55	9.65	11.36		
On the run premium	5.65	9.10						
Roll	25.12	9.10	31.19	10.55	1.26	11.36		
Turnover (negative)	34.26	9.10	16.50	10.55	16.50	11.36	12.23	12.35