Corporate Liquidity under Basel III: The Credit Line Channel *

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PRELIMINARY AND INCOMPLETE

Abstract

The Basel III Liquidity Coverage Ratio (LCR) rule imposed an unprecedented liquidity requirement on U.S. banks and increased their costs of maintaining credit lines. I show that banks tend to pass on their increased costs to borrowers and are curtailed in their ability to originate credit lines. I introduce novel metrics drawn from a machine learning analysis of contractual agreements, and further show that banks retain greater control in credit lines. The net result is a decline in credit line origination and a market that is unfavorable to borrowers. Financially unconstrained firms largely contribute to borrowing declines and turn to debt-financed cash for corporate liquidity, rendering them riskier. My results reveal important changes to corporate liquidity preferences and risk profiles when intermediation is costly.

KEYWORDS: Liquidity Coverage Ratio, Credit Lines, Shadow Banking
JEL CLASSIFICATION: E5, G21, G23, G28, L5

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1 Introduction

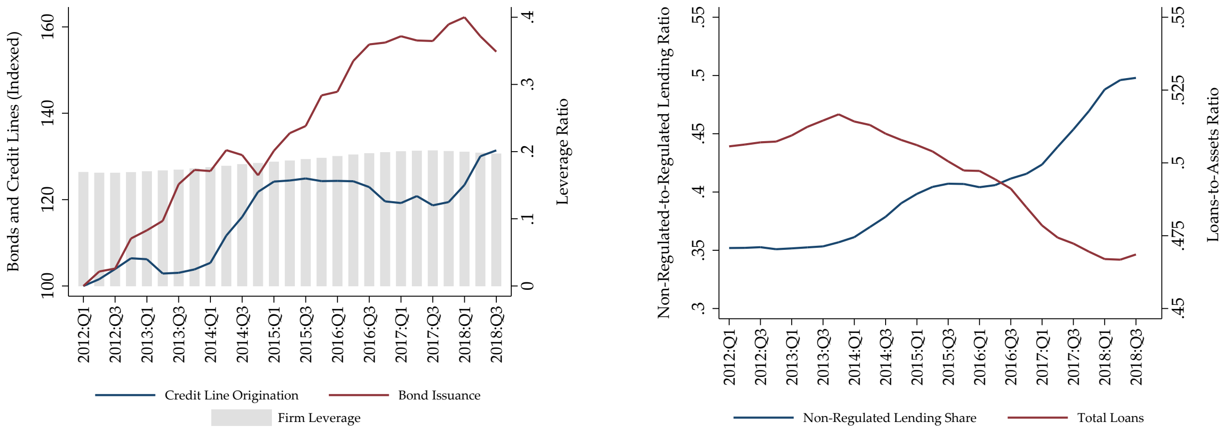
Beginning with the classic work of Diamond and Dybvig (1983), the illiquidity of banks' assets has been understood to play a crucial role in spurring banking crises. With Basel III, regulators sought to address illiquidity in the banking system by including an unprecedented liquidity regulation termed the Liquidity Coverage Ratio (LCR) rule. This regulation requires banks to hold high-quality liquid asset buffers to fulfil future credit line drawdowns and other obligations.[1] While the necessity and efficacy of the regulation is still under debate (e.g., Allen and Gale (2018), Bai et al. (2018), Calomiris et al. (2015), Diamond and Kashyap (2016), Thakor (2018)), I show that an important consequence was a decline in banks' credit line origination.

In this paper, I investigate myriad effects of LCR-imposed liquidity costs on credit line lending terms, borrower liquidity policies and ensuing firm real outcomes. Credit lines represent important corporate liquidity management tools (Holmström and Tirole (1998)) and are relatively inexpensive compared to cash-based liquidity (Nikolov et al. (2019)). Under the LCR paradigm, however, banks incur higher funding costs, which they tend to pass on to their borrowers (Khwaja and Mian (2008)).[2] Credit lines, therefore, no longer remain the same inexpensive source of corporate liquidity. I investigate these implications of the LCR regulation by assembling a comprehensive bank–loan–borrower–time panel incorporating granular data on banks' risk and liquidity positions from the FR Y-9C regulatory database. The data allow me to simultaneously study the effects of aggregate market dynamics, linking them to lender–specific characteristics and investigate the consequences to borrower–level outcomes. I extend the scope of the data even further by linking loans to their underlying contractual agreements by parsing borrowing firms' SEC filings. With these contracts, I explore changes in credit line contracting and bargaining power by introducing novel metrics drawn from recent advances in machine learning.

I first present aggregate dynamics of the credit market in Figure 1, from which the impact of the LCR rule on credit line origination is immediately apparent. Panel A shows that firms' bond issuance grew almost steadily between 2012:Q1 and 2018:Q3, as did firm leverage, indicating little change in firms' appetite for debt in this period. The dynamics of credit line borrowings stand in stark difference — the growth stagnates beginning 2015:Q1, and remains at this level for the subsequent three years. The slight upward trend in 2018:Q3 coincides with the partial repeal of LCR. In parallel, Panel B reveals a substantial growth in the share of *non-regulated*

[1] High-quality liquid assets (HQLA) are defined exogenously by regulatory agencies based on their expected availability and price resiliency during crises. HQLA constituents include inherently low-yield cash reserves and high credit-rated government and corporate bonds. See Section 2 for a detailed discussion.

[2] Unlike capital adequacy ratios, which require changes to banks' equity composition and raise their cost of capital in violation of Modigliani-Miller (e.g., Fraisse et al. (2020), Kisin and Manela (2016)), liquidity regulations directly affect banks' asset composition. The resulting impact is on *asset* returns and hence capital-structure agnostic.



(A) Aggregate Credit Demand

(B) Compositional Dynamics

Figure 1. Aggregate Credit Market Dynamics. This figure plots the four-quarter rolling average of debt borrowings by firms and the compositional dynamics of lenders in each quarter between 2021:Q1 and 2018: Q3. Panel A depicts the credit line borrowing by all U.S. firms in the Thomson-Reuters' DealScan sample and contrasts it with aggregate quarterly bond issuance, along with the average leverage ratio of U.S. non-financial firms in the Compustat sample. The series are indexed to 100 as of 2012:Q1. Panel B presents the share of credit line borrowing that are originated by non-regulated lenders (in blue) and the average loan-to-assets ratio of U.S. banks (in red).

lending, which increased from one-third in the initial periods to more than half in the latter.[3] The increase in non-regulated lending, accompanied by an overall stagnation, indicates that banks significantly cut back on their credit line lending over the period.[4] Overall, the figure reveals that the dynamics of credit line demand are distinct from debt — the observed stagnation is unique to bank–originated credit lines. Through my empirical analyses, I attribute these dynamics to a shift in firm liquidity preferences with the advent of bank liquidity regulation.

I define a difference-in-differences empirical framework incorporating levels of treatment within LCR-covered banks, mapping credit line market outcomes to salient features of LCR's implementation. I include additional treatment dosage levels corresponding to transition phases of LCR. I employ a rich set of controls that capture banks' funding positions and risk-sharing, and borrower– and loan–characteristics, along with fixed effects that account for unobserved heterogeneity at various levels. In the base specification, I study the differential impact of LCR on banks facing the highest marginal costs of funding new credit line commitments. Such banks, when initiating new credit lines, incur the highest marginal costs due to HQLA holdings.

I find that highly exposed banks reduce their new credit line lending significantly more — by 52.11% of the pre-LCR mean — as compared to banks with low exposure to the regulation. They

[3] *Non-Regulated* lenders are DealScan lenders that do not file FR Y-C reports. Banks not covered in these data include small BHCs (total assets less than \$3 billion), non-bank financial institutions, and non-U.S. BHCs. LCR-covered banks comprise 98% of *bank–driven* credit line originations in the DealScan data.

[4] The increase is also consistent with the findings of Buchak et al. (2018) and Berlin et al. (2020) who find an increase in non-bank lending in the retail and wholesale credit markets.

simultaneously increase the all-in undrawn spread associated with new credit lines by 25.7% relative to those with low commitments. This abnormal increase in undrawn spreads prevails despite controlling for borrowers' creditworthiness and points directly to banks passing on increased funding costs to their borrowers. Notably, the magnitude of these effects increases with each phase of the LCR regulation.[5] Simultaneously, I find a 64% within–lender increase in credit line origination by non-regulated lenders following the LCR regulation, consistent with the aggregate dynamics depicted in Figure 1. This increase is attributable to a migration of existing bank–borrowers to non-regulated lenders, who offer lower spreads and form new lending relationships. Consequently, a larger fraction of U.S. corporations rely on the non-regulated banking system for their liquidity needs.

The above results reveal a broad shift in syndication structures with a transfer of corporate liquidity creation from regulated to non-regulated intermediaries. I show that this shift constrains firms' access to liquidity even during normal, *non-crisis* periods through a firm-establishment–level geographical analysis. LCR-covered banks cut back on liquidity creation across the country, with non-regulated lenders filling this gap only around major U.S. financial centers. I also find evidence of an aggregate increase in lending strictness with both non-regulated and highly committed banks increasing the usage of covenants in credit line packages.

In my next set of analyses, I go deep into the evolving nature of credit line contracts, by introducing novel measures of bargaining power of banks in the bank–borrower relationship. These measures, constructed employing natural language processing (NLP) tools, reflect the *soft*-information content embedded in contract texts. The first dimension that I consider, *Borrower Constraints*, is a measure of binding clauses imposed on the borrower in the contract. I construct this measure by identifying sentences in the document that apply constraining phrases pertaining to the borrower. The corresponding analysis shows that following the LCR rule, liquidity-constrained lenders increase constraints on the borrower, signaling an increased concentration of bargaining power with lenders. I then analyze the usage of clauses that allow lenders to retain greater control and recourse to payments in the event of borrower default. To capture these dynamics, I create measures of *Early Termination Clause* and *Seniority Clause*, which are probabilistic measures of the agreement containing either of these clauses. I find that liquidity-constrained lenders increasingly favor the use of these clauses following the LCR regulation. Finally, I construct the *Document Complexity* metric by measuring the *local word*

[5] A major development that parallels the timeline of the LCR regulation is the phasing in of increased Basel III capital adequacy requirements. In Appendix D, I compare the differential credit line lending activity of capital-adequacy–constrained banks, by conditioning banks based on their aggregate loan exposures. Were the observed credit line outcomes driven by capital requirements, such a comparison should yield results analogous to those obtained under commitment–based conditioning. I find that loan-exposure–based conditioning does not indicate any statistical or economic significance in the differential credit line origination activity. Thus, the effects that I document appear to be driven by liquidity regulation, rather than capital adequacy requirements.

entropy, which is an information-theoretic measure of the linguistics of the text.[6] I find that the complexity of contracts increases significantly for lenders with high credit line commitments. This result indicates that lenders with higher liquidity constraints place increased emphasis on creating loan-specific contracts for credit lines, rather than rely on standard contract templates.

The above set of results reveal an aggregate decline in syndicated credit line lending following the LCR rule, which could alternatively be driven by: (1) credit rationing by banks, owing to higher origination and maintenance costs, or (2) reduced firm appetite for credit lines following unfavorable spreads and lending terms. To resolve the above dichotomy, my next set of analyses explores how various financial characteristics at the borrower–level affect their decision to borrow credit lines. I first categorize firms based on their access to financial markets, since financing constraints directly impact firms' decision to borrow credit lines (see Berger and Udell (1995)). I find that unconstrained firms, with access to alternate forms of liquidity, reduce their credit line borrowings by more than their constrained counterparts.[7] Within the sample of unconstrained firms, I find consistent evidence that firms with the highest ability to adapt their liquidity policies — those with high current portions of long term debt, high levels of innovation, and low default risk — reduce their credit line borrowings the most. The aggregate credit line declines, therefore, appear to be driven by firms' changing liquidity policies in response to unfavorable lending terms.[8]

I show that changes in firms' liquidity policies have multiple ramifications on their risk and performance. The presence of credit lines and accompanying bank monitoring has important consequences to its cash holdings (Acharya et al. (2013)), cashflow volatility (Sufi (2009), Disatnik et al. (2014)), financial leverage, and default risks (Norden and Weber (2010)). I analyze various financial characteristics on the extensive margin of firms that continue to borrow credit lines *vs.* firms that do not. I find that the latter cateogry of firms primarily switch to debt-financed cash to meet their liquidity requirements, and in doing so are more sensitive to the stock market and at greater risk of default. Further, in the absence of monitoring, these firms show higher profitability and are more innovative with higher capital and R&D investments. These firms also increase payouts to shareholders, suggesting a wealth transfer from debtholders to shareholders. Broadly, these results reinforce a central theme that emerges from

[6]Higher entropy indicates lower information content per word of the document, or in other words, more verbose and overtly defined contracts (see also Shannon (1951), and Bentz et al. (2017)). Legal documents prepared on a case-by-case basis have been shown to have higher entropies than those based on standard codified rules (see, e.g., Friedrich et al. (2020) and Friedrich (2021)).

[7]My primary measure of constraint is size-age index (cf. Hadlock and Pierce (2010)). I also validate the results under alternative measures of financing constraints.

[8]The converse argument where this contraction is driven by banks' selectivity in lending would imply that unconstrained firms *gain* the most in terms of their share of credit line lending, which is contrary to my findings.

the gamut of results — while banks have altered the terms under which they initiate credit lines, the aggregate decline in the market for credit lines is an attribute of firm-driven preferences.

My work adds primarily to the literature surrounding the implications of bank liquidity regulation and lending outcomes. I contribute to this literature by measuring the LCR-driven real outcomes for firms and show that observed lending declines are driven by evolving firm financial policies. Early works measuring the liquidity of the banking system, with implications on the optimal form of regulation include Berger and Bouwman (2009), and Bai et al. (2018) and provide alternate measures of estimating bank liquidity. Theoretical works, including Allen and Gale (2018), Calomiris et al. (2015), Carletti et al. (2020), Diamond and Kashyap (2016), Farhi et al. (2009), and Kashyap et al. (2020), examine the interplay between capital and liquidity regulation. They propose versions of the optimal regulation and are divided with regards to the ex ante effectiveness of LCR. Few works directly looking at the impact of LCR on banks include Macchiavelli and Pettit (2018) who report positive impacts of LCR on the liquidity composition of broker-dealers; Roberts et al. (2018) who show that LCR caused banks to create less liquidity (measured in terms of *market* liquidity of assets and liabilities); and Sundaresan and Xiao (2018) who find evidence that LCR caused a decline in loan growth of covered banks and a flow of loan-origination to non-regulated banks. The last work is closest to this paper, although they focus on the liquidity impact (measured through loan originations) on banks alone. My work provides a novel implication on the evolution of syndication structures in response to the liquidity regulation, and the implications to *corporate* liquidity through the credit line channel.

I also add to the literature on the propagation of bank liquidity shocks to firms. I provide a novel perspective of firm responses to costly, intermediated corporate liquidity during *normal* times when alternate options are more accessible. Khwaja and Mian (2008), Chava and Purnanandam (2011), Chodorow-Reich (2014), Iyer et al. (2014), and Acharya et al. (2018) among many others investigate this transmission in terms of lending through specific banks affected by crisis episodes. Among these, Campello et al. (2011) specifically focus on corporate liquidity in the aftermath of the Global Financial Crisis. Other works including Gropp et al. (2019), and Fraisse et al. (2020) establish a link between firm real outcomes and banks' capital constraints. In this paper, I focus on banks' liquidity constraints that distinctly impact their ability to originate credit lines.

2 Background on Bank Liquidity Regulations

The Basel III framework (B3) proposed by the Basel Committee on Banking Supervision (BCBS) signifies the most comprehensive overhaul of prudential regulations following the 2007-09 financial crisis. Along with strengthening and enhancing the capital requirements of banks (which were introduced with Basel I and modified in Basel II), B3 included recommendations for an unprecedented liquidity requirements on banks. These liquidity requirements are presented in the form of Liquidity Coverage Ratio (LCR), and the Net Stable Funding Ratio (NSFR). The LCR is the first liquidity standard to be implemented in the history of banking regulation and is designed to keep banks liquid in the short-run (over 30 days), while NSFR (which was implemented subsequently) addresses banks' long-run structural asset and liability mismatches. The LCR seeks to achieve its goal by requiring that banks hold sufficient High-Quality Liquid Assets (HQLA) to meet their 30-day expected cash outflows.

The BCBS finalized its standardized recommendation of these rules in January 2013, although the actual implementation of the rules was left to prudential authorities of member countries. The U.S. proposed a customized version of the rules in October 2013 and invited comments from participants, before finalizing the rule in September 2014, with substantial revisions to its scope. It is also important to note that the customized U.S. version was more stringent than the BCBS recommendations — in fact, the Eurozone implementation allowed for a longer transition period for the requirements, and less restrictive calculation of the ratio.

The U.S. LCR requirement applies to all banks with more than \$250 billion of assets in its standard form, described below. For banks with assets between \$50 billion and \$250 billion, a modified version was applied, where the denominator is set to 21-day net cash outflow (rather than 30-day). LCR does not apply to banks with assets less than \$50 billion, unless: (1) they are depository subsidiaries of bank holding companies (BHCs) that meet the above LCR requirements and have assets of more than \$10 billion; or (2) have on-balance sheet foreign exposure of greater than \$10 billion.

$$LCR \equiv \frac{\textit{Stock of High Quality Liquid Assets}}{\textit{Net Expected 30-day Cash Outflow}} \geq \textit{Compliance Threshold} \tag{1}$$

The numerator is the total stock of HQLA held by the bank. Assets qualifying as HQLA are determined by the regulation based on their quality and market liquidity, and are categorized as Level 1 and Level 2 assets. Level 2 assets carry non-zero haircuts to market value and cannot constitute more than 40% of the HQLA stock. Eligibility of assets as HQLA is determined exogenously by the Office of the Comptroller of the Currency, Treasury; Board of Governors of the Federal Reserve System; and Federal Deposit Insurance Corporation. Additions and modifications to the list of HQLA involves publication of the proposed changes and an invitation for comments, before it is officially published in the Federal Register.[9] The denominator is calculated based on a prescribed set of run-off rates including, among other items, credit line drawdows and deposit withdrawals. Run-off rates are again assigned by the above Agencies and are determined based on the type of obligation and whether the obligee is a government, financial or non-financial institution — the corresponding rates increasing in the same order. Notably, the credit worthiness of the borrower does not impact the calculation of expected withdrawal. The right-hand side of the inequality, *Compliance Threshold*, was prescribed in phases following a transition period as follows — 80% as of January 1$^{\text{st}}$, 2015; 90% as of January 1$^{\text{st}}$, 2016; and 100% as of January 1$^{\text{st}}$, 2017. The regulation was modified in May 2018 to exclude banks with assets less than $100 billion.

The LCR regulation has important consequences to banks' asset returns. The liquidity-based selection of HQLA inherently translates to lower returns (Pástor and Stambaugh (2003)). Banks therefore face diminished return on their assets when required to increase HQLA composition on their balance sheets. In particular, undrawn credit line commitments, which are off-balance sheet items, incur additional funding costs since LCR requires banks to cover near-term expected drawdowns with balance sheet assets. This imposes a unique constraint on banks by limiting their ability to maintain credit line obligations by increasing their costs of funding undrawn credit lines commitments.

3 Data and Main Variables

3.1 Data

I assemble a comprehensive bank-loan-borrower panel that links syndicated credit line origination with regulatory information on banks, and firm characteristics, by drawing upon a number of data sources. Data on syndicated loan origination are obtained from WRDS-Thomson-Reuters' LPC DealScan (DealScan). I obtain data on origination dates, notional amounts, the lender's share of the loan, lead arranger status, maturities, all-in drawn and undrawn spreads, data on financial and net worth covenants, loan types and lender and firm identifiers. I restrict the sample to include only credit line type loans in the period 2012:Q1 to 2018:Q4.

Regulatory data on banks are from a database of FR Y-9C filings maintained by the Federal Reserve Bank of Chicago. These are compiled from granular quarterly filings of all U.S. bank holding companies (BHCs) with assets of more than $3 billion. Banks in the FR Y-9C data are identified by the RSSD ID, which is a unique identifier assigned to institutions by the Federal

[9] Level 1 assets include cash, central bank reserves, central bank debt, and marketable debt issued by governments and public sector entities that carry 0% risk weights. Level 2 assets include corporate and covered bonds rated AA– or higher, and sovereign debt with risk weights <20% (see Appendix Table A.1 for HQLA composition).

Reserve Board. The Fed also provides a mapping between subsidiary RSSD ID's and the parent BHC. I match subsidiary-level identifiers between banks in the FR Y-9C data and lenders in the DealScan data based on the name and city of incorporation, since no such link readily exists. I then link these matched lenders to their parent BHC using the above mapping scheme. In these matched data, banks covered by the LCR (or assets ≥ \$50 billion) comprise the vast majority and cumulatively account for over 98% of credit line originations, and I restrict the sample to these banks without loss of generality (see also Chodorow-Reich (2014)). Lenders that do not file FR Y-9C account for 45% of cumulative credit line originations. With these restrictions, the data yields observations on 18,851 loans corresponding to 10,844 lender–quarter observations, which corresponds to an average of 6.25 lenders in a syndication structure. LCR-impacted banks constitute 5,367 bank–quarter observations.

For public borrowers in the sample, I obtain the corresponding lending contract by examining firm filings on the SEC Edgar database. I use a machine learning-based classification scheme to identify contracts attached as exhibits to 8-K, 10-K and 10-Q filings. I train the algorithm on a set of manually selected credit line contracts and use it to classify exhibits into (1) contracts and non-contract exhibits; and (2) if it is a contract, whether it corresponds to a credit line agreement, based on a title match. I manually verify these selected contracts and map them to DealScan credit lines by extracting the borrower name and loan start date.[10]

Data on firm characteristics are from Compustat and matched to DealScan using the linking scheme provided by Chava and Roberts (2008). The latest update of the linking table at the time is based on a December 2017 extract, and I extend this match until 2018:Q4. Share price data used in calculating beta and implied default probabilities are obtained from CRSP. To classify firms based on their innovation, I employ data on the Total *Q* introduced by Peters and Taylor (2017). I also use data on firm patent filings, which are provided by Kogan et al. (2017). Establishment-level data on employment are from Your-economy Time-Series (YTS), maintained by the Business Dynamics Research Consortium at the University of Winsconsin. I aggregate these base data at various levels corresponding to the empirical specification under investigation. I describe the key outcome variables and levels of aggregation in the following section.

3.2 Variable Construction and Measurement

3.2.1 Bank Credit Line Origination

In the base tests, where I investigate the effect of LCR on credit line origination and lending relationships, I collapse the data into a bank–quarter panel. I construct the dependent variables

[10]Nini et al. (2012) propose an alternative rule-based approach to identifying loan contracts. I find that my ML-based approach results in an increased number of matches.

as follows. *Quarterly CL Lending* is the total dollar value of credit lines originated by the bank in a given quarter, scaled by one-quarter lagged total assets. I obtain the dollar value of credit line by multiplying the facility amount by the fraction of the loan attributed to the given bank (both reported in DealScan). I compute this measure for non-regulated borrowers by scaling by one-quarter lagged industry–average assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of credit line deals originated by the bank, as a lead arranger, in the given quarter. The benefit of this measure is that it retains deals for which the composition of lenders is not reported on DealScan and applies uniformly to regulated banks and non-regulated lenders.

The next two variables focus on lending relationships and are calculated analogously. *New Borrower CL Lending* is the total dollar value of credit lines extended to bank-specific new borrowers by a given bank in a given quarter, scaled by one-quarter lagged total assets. I identify these bank-specific new borrowers at the bank–borrower–quarter level as those that borrow from a given bank for the first time in the DealScan panel (beginning in 1986). *New Borrower CL Origination Count* is similarly defined as the logarithm of one plus the number of CL deals corresponding to a bank-specific new borrower.

3.2.2 Loan–level Characteristics

I analyze the price effects of LCR using a loan–level panel to allow for the use of lender– and borrower–fixed effects and control variables. *Undrawn Spread* is the logarithm one plus the all-in undrawn spread (in basis points) reported on DealScan. Similarly, *Drawn Spread* is the logarithm of one plus the all-in drawn spread (in basis points). There are advantages to studying both these measures simultaneously. While the borrower's credit worthiness plays a large part in the determination of both spreads, the *Undrawn Spread* reflects to a large extent the costs incurred by the bank in funding the undrawn portion of the credit line, in addition to the option premiums (e.g., Berg et al. (2016)).

3.2.3 Contractual Strictness

The next set of dependent variables capture the strictness of lending terms in terms of covenants and collateral. Covenants apply to the package constituting the loan, rather than the loan itself. Accordingly, the variables on covenant terms are defined at the package level. $\mathbb{1}$*(Covenants)* is an indicator variable that takes the value of 1 for loan packages that include at least one covenant, financial or net worth, and 0 otherwise. *#Covenants* is the logarithm of one plus number of financial covenants included in the loan package. *Initial Covenant Slack* is the average absolute value of the percentage difference between the covenant threshold and initial level of the corresponding ratio. $\mathbb{1}$ *(Secured)* is a categorical variable taking the value of 1 for credit lines that are secured and 0 for unsecured credit lines.

3.2.4 Contract Textual Variables

I define a number of variables based on a machine learning analysis of credit line contracts, which I obtain from firms' SEC filings. I do so using tools from the domain of natural language processing (NLP). The variables capture the degree of lenders' risk aversion and indicate the relative bargaining power between lenders and borrowers.

Borrower Constraints. My first textual variable captures the relative extent of bargaining power of banks relative to borrowing firms. I measure these restrictions by counting the usage of constraining language in the credit line agreement that pertain to borrowers. The rationale behind this metric is that the higher the bargaining power of firms, the more the number of restrictions on the borrower. This is represented in the variable *Borrower Constraints*, which is constructed as follows. First, for each sentence, $S \in \{\mathbb{S}_S\}$, in the agreement I look for the usage of legal words and phrases denoting constraining language and accordingly classify them into *Constraining* and *Non-Constraining*, to assemble the set $\{\mathbb{C}_S\}$ of constraining sentences.[11] For each sentence $S \in \mathbb{C}_S$, I construct a dependency tree to identify the word to which the constraining clause applies (this could alternatively be the *subject* or the *object*, depending on the semantics of the particular sentence), using a part-of-speech (POS) tagging algorithm. I then identify those sentences where the constraining phrase applies to the borrower — in legal documents this is referred to by either (1) the word "borrower" (or variations thereof), (2) name of the borrower, or (3) name of the parent company of the borrower. I obtain the latter using Named Entity Recognition (NER) on the agreement. This gives the set $\mathbb{B}_S \subseteq \mathbb{C}_S$ of constraining sentences that directly pertain to the borrower. With this, I define the within–document metric of borrower constraint as the logarithm of one plus the ratio of number of borrower-constraining sentences (the set $\mathbb{B}$) to total number of constraining sentences in the document (the set $\mathbb{C}$), for document i:

$$\textit{Document Borrower Constraints}_i = \log\left(1 + \frac{|\mathbb{B}|}{|\mathbb{C}|}\right). \tag{2}$$

I introduce the logarithmic transformation to account for the fact that empirically the raw metric has a skewed distribution. Finally, I construct the bank-quarter–level metric by averaging the above measure across all credit lines ($N_{l,q}$) originated by a bank l in a given quarter q:

[11] The corpus of constraining words and phrases is obtained from an open-source repository of legal language maintained by ContraxSuite™, a provider of ML–based contract review software to major law firms.

$$Borrower\ Constraints_{l,q} = \frac{1}{N_{l,q}} \sum_{i \in N_{l,q}} Document\ Borrower\ Constraints_i \tag{3}$$

Early Termination and Loan Seniority. The next two measures capture the propensity of lenders to include Early Termination and Seniority Clauses in the contracting agreement. Early Termination clauses give the lender the right to call the credit line early, thereby minimizing their cash outflow obligations in the event of a liquidity shock. Seniority clauses come to the fore in the event of borrower default and assure banks of higher recoveries in court-mandated settlements, or eventual firm liquidation. Both of these clauses minimize liquidity runs on the bank and mitigate the backpropagation of firm liquidity shocks to the bank, and on to its other obligees. I use a probabilistic measure to gauge the presence of these clauses in the loan agreement. A naïve approach would involve looking for the corresponding clause titles in the document. The problem with this approach, however, is that with increasing legal complexity of the document, the definitions and language surrounding these clauses are ever evolving. The approach I use helps circumvent this problem, although I do acknowledge that this increased scope comes at the cost of *precision*.

The method I employ to define *Early Termination Clause* (and identically, *Seniority Clause*) is as follows. I start with a corpus of sample usage of early termination clauses that I identify manually from a set of credit line agreements. Denote this corpus of sample clauses, c by the set $\{\mathbb{U}_c\}$. I divide each document into a set $\{\mathbb{D}_p\}$ of paragraphs, p. I compute the measure of probability that the document contains an early termination clause as the *maximal* cosine similarity between each paragraph $p \in \mathbb{D}$ and each sample clause $c \in \mathbb{U}$.[12] Let $\mathbf{v}_p$ and $\mathbf{v}_c$ denote the vector representations of p and c, respectively. Then, the pairwise cosine similarity, $Sim : \mathbb{D} \times \mathbb{U} \mapsto \mathbb{S}$, between p and c is obtained as follows:

$$\cos\theta_{p,c} = \frac{\mathbf{v}_p \cdot \mathbf{v}_c}{||\mathbf{v}_p||||\mathbf{v}_c||}, \tag{4}$$

with $\{\mathbb{S}_{p,c}\}$ denoting the resulting set of cosine similarities. The maximal cosine similarity, which gives the within–document measure, is the maximum value of the set $\mathbb{S}$, or:

$$Document\ Early\ Termination = \max(\cos\theta_{p,c})_{s_{p.c} \in \mathbb{S}} \tag{5}$$

[12]Cosine similarity is the cosine of the angle between the vector representations of two texts. A cosine similarity of one (zero) indicates perfect overlap (no overlap). See Campello et al. (2021b), and Hoberg and Phillips (2016).

Then, I calculate the bank-quarter–level metric by averaging the above measure across all credit lines ($N_{l,q}$) originated by a bank l in a given quarter q:

$$\textit{Early Termination}_{l,q} = \frac{1}{N_{l,q}} \sum_{i \in N_{l,q}} \textit{Document Early Termination}_i \tag{6}$$

The analogous variable, *Seniority Clause* is obtained following an identical method based on a sample set of seniority clauses for $\mathbb{U}$.

Document Complexity. My last textual metric is *Contracting Complexity*, which measures the complexity of contracting agreements in terms of the information content represented by words within the context in which they are employed. I do by constructing a measure of *local entropy*, which I estimate using the probability distributions generated by the Word2Vec algorithm, which is a neural network based vectorization scheme for texts. At its core, this algorithm generates a probability distribution for each word representing the probability that it is sampled within the context of the text.[13] The method I employ is adapted from Friedrich et al. (2020) and is given as follows. Denoting each token (word) of the text ($\{\mathbf{T}_i\}$) as w_i, Word2Vec creates a high-dimensional vector representation $\mathbf{u}_i$ and processes it via a two-layer neural net to generate the embedded (lower dimension) output vector $\mathbf{v}_i$. Let N be the dimension of the latter vector space. At the core of this transformation lies a distribution of posterior probabilities (μ_{w_j}) over all words $w_j \in \mathbb{T}$ in the text associated with each input vector ($\mathbf{u}_i$). This probability distribution is generated by a partitioning function, $f(\mathbf{u}_i) = \mathbf{v}_i$ within the hidden layer (remaining inaccessible). However, the skip-gram architecture does output the vector notations, with which the probability of any word (w_0) being associated with the context of a given word w_i, is calculated as:

$$p(w_0|w_i) \equiv \mu_{w_i}(w_0) = \frac{e^{\mathbf{v}_0^T \mathbf{u}_i}}{\sum_{j=1}^{N} e^{\mathbf{v}_j^T \mathbf{u}_i}}. \tag{7}$$

The local entropy, H associated with a given word w_i, can be computed using the above conditional distribution as:

$$H(W_i) = -\sum_{j=1}^{N} p(w_j|w_i) \cdot \log_2(p(w_j|w_i)), \tag{8}$$

which results in an entropy distribution corresponding to the universe of words. Note that the base-2 logarithm implies that the resulting measure carries a unit of *bits/word*. For com-

[13] Word2Vec offers two embedding schemes — Continuous Bag of Words (CBOW) and skip-gram. CBOW predicts a missing word given the context, while skip-gram predicts the context words given the target word. The derived probability distributions accordingly have different interpretations. I use the skip-gram distributions, which represent the probability that a word is sampled from within the context *vs.* randomly sampled.

putational reasons, I construct this measure within estimation blocks of five words in each document (Schürmann and Grassberger (1996) show that this window size is optimal). I define within–document entropy measure as the logarithm of one plus the mean of the above distribution. Finally, averaging the above metric across all contracts generated by a bank in a given quarter results in the bank–quarter level measure of *Contracting Complexity*.

3.2.5 Firm Credit Line Borrowing and Outcomes

To analyze the impact of LCR on corporate liquidity policies and resulting outcomes, I aggregate the base data by borrowers, resulting in a firm–quarter panel. The primary dependent variable on the firm side is *Quarterly Borrowing*, which is the sum of facility amounts of credit line borrowing by the firm, in the quarter, scaled by one-quarter lagged total assets of the firm. *WA Maturity* is the logarithm of one plus the facility amount–weighted average of the number of years between the start and end dates of the facility. Analogously, *WA Drawn (Undrawn) Spread* is the logarithm of one plus the facility amount–weighted average of the all-in drawn (undrawn) spread, in basis points. In these firm-side analyses, I collapse spreads at the firm–quarter level in order to capture the aggregate borrowing costs faced by the firm in the quarter.

In addition, I employ a number of variables corresponding to firm financial policy, risk factors and real outcomes. *Net Cash* is cash and short-term investments net of current liabilities, scaled by total assets. *Net Leverage* is the total short- and long-term debt net of cash divided by total assets. I calculate *Cashflow Volatility* following Minton and Schrand (1999) as the coefficient of variation in the quarterly operating cashflow, over the preceding 24 quarters (six years). *Asset Beta* is calculated by unlevering quarterly stock market beta, estimated using CAPM. I estimate *Default Probability*, which is the physical probability (or expected default) based on Merton's distance to default, using the methodology of Bharath and Shumway (2008), on the last day of the preceding quarter. *Profitability* is net income divided by lagged total assets. *New Patents* is one plus the logarithm of number of patent applications by the firm in the quarter. *R&D Spending* is quarterly research and development expenses scaled by total assets. *Investment* is capital expenditures divided by total assets. *Payout Ratio* is the sum of annual dividends to common and preferred shareholders, plus repurchases, scaled by the operating income. All of these variables computed from CRSP/Compustat data are winsorized at the 5% and 95% levels.

3.2.6 Conditioning Variables

Several characteristics of lenders and borrowers may impact their credit line lending and borrowing choices and I proxy for these factors through a set of conditioning variables.

Bank Liquidity Funding Costs. My first conditioning variable captures the intensity of LCR's impact on covered banks. *High Commitment* is an indicator variable that takes the value of 1 for each bank in the highest within–quarter tercile of the ratio of undrawn commitments to assets, and 0 for those in the lowest tercile. Banks with *High Commitment* set to 1 face the highest marginal costs of originating credit lines — for these banks, a higher fraction of their asset base is devoted to lower-return HQLA. This variable captures the level of banks' exposure to LCR. I next condition banks based on their regulatory status. *Non-Regulated* is a dichotomous variable that is set to 1 for lenders in the DealScan that are outside the purview of LCR. These include lenders who do not file FR Y-9C regulatory disclosures, and banks that do not meet LCR's $50 billion asset threshold, and hence remain unimpacted. Conversely, the indicator is set to 1 for banks that meet this asset threshold and file regulatory disclosures.

Firm Borrowing Relationships. Firms' relationships with banks play an important role in determining their access to bank borrowings (e.g., Berger and Udell (1995)). Further these relationships tend to be sticky owing to the cost of acquiring private information on borrowers (Chodorow-Reich (2014)). I capture this relationship dynamic at the firm–quarter level through the indicator variable *New Borrower*. The variable takes the value of 1 for firms that borrow credit lines for the first time from the syndicated lending market in the given quarter. Banks' cost of acquiring private information is highest for these new borrowers and is not mitigated by sharing risk with co-syndication agents. Conversely, the variable is set to 0 for returning credit line borrowers, matched within industry and within lagged quarter on firm characteristics including size, financial leverage, profitability, Tobin's *Q* and investments.

In addition, I introduce firm-level conditioning that account for the impact of LCR on borrowing relationships. I define *Non-borrower* as a firm that exits the syndicated lending market for credit lines following full implementation of LCR on January 1st, 2017, and did not borrow for three years preceding this date. This variable takes the value of 1 for such firms and 0 for firms that continue to borrow syndicated credit lines following this period.

Firm Financial Characteristics. Financial characteristics of a firm shape their liquidity policies. In the baseline borrower analyses, I condition firms on their financial constraints based on the size-age index of Hadlock and Pierce (2010). The SA index is particularly suitable as a measure of constraint since it characterizes the ability of firm to raise new capital and does not directly imply *operating* constraints. With this measure, I define the variable *Unconstrained Firm* to take the value of 1 for firms in the lowest tercile of the SA index and 0 for those in the highest tercile (higher values of the index imply higher constraint).

Other variables conditioning on firm characteristics are constructed as follows. *Debt Due in 1 Year* is the one-quarter lagged current portion of long term debt, scaled by total assets. *Tangibility* is defined following Berger et al. (1996) and Almeida and Campello (2007) as *0.715*×

Receivables + 0.547 × *Inventory + 0.535* × *Capital.* Finally, *Innovation* is the total Q measure, based on firms' innovation capital (cf. Peters and Taylor (2017)).

3.2.7 Control Variables

I account for a number of variables that have implication on banks' credit line origination, credit line pricing and firms' borrowing preferences. At the bank level, I control for lagged assets, net financial leverage (net debt divided by assets) and loan to assets (total loans to total assets). At the loan-level, I control for maturity (logarithm of one plus number of months to maturity), and the facility amount. I also control for risk-sharing in the syndication structure through the use of *Co-Syndication Agents*, which is one plus the logarithm of within–quarter average of number of lenders in the syndication structure. At the borrower-level I control for the lagged size (logarithm of total assets), age (years since IPO), Tobin's Q, profitability, net financial leverage and net worth (non-cash total assets minus total liabilities, divided by non-cash assets). In specifications estimating firm real outcomes, I exclude controls that coincide with the dependent variable.

4 Summary Statistics and Empirical Methodology

4.1 Summary Statistics

I present descriptive statistics for the variables described in Section 3.2 in Table 1. I aggregate the base data alternatively in terms of bank-quarter–level, borrower-quarter–level, or deal package–level in my empirical estimations. While most of these data have observations in order of a few thousands, my tercile-based conditioning and varying identification periods mean that the actual number of observations in each empirical test is smaller than this sample size. Borrowers in my sample are all public firms who report data on all outcomes and controls on Compustat. The resulting panel is comparable in size to the few studies linking DealScan to FR Y-9C data and public firms (e.g., Chodorow-Reich (2014)), adjusting for timeline differences. Lenders in my sample originate credit lines averaging to \$1.49 per \$1,000 of assets in each quarter (*Quarterly CL Lending*). In the pre-LCR period this mean was \$1.65, which already indicates the impact of LCR on aggregate credit line origination. For covered banks the pre-LCR mean was much higher at \$4.54, although in the post period this converges to \$1.62, in line with non-regulated banks. I account for this pre-period disparity in my regressions with the use of lender fixed effects (Section 4.2). In terms of *Quarterly CL Origination Count*, the corresponding means are 1.73 for the full period, and 1.70 in the pre-LCR period for all lenders (1.72 for covered banks). I discuss the pre-LCR means for other variables in the corresponding sections of results.

TABLE 1 ABOUT HERE

4.2 Empirical Specifications

The timeline of my empirical tests begins in 2013:Q1 and proceeds until 2018:Q2, which marks the partial repeal of the regulation. As a baseline, I estimate the impact of LCR on bank credit line origination, conditioning on their *relative* levels of exposure to liquidity drawdowns, HQLA holdings and the regulation itself. I modify subsequent specification to focus on firm credit line borrowing and outcomes, on the intensive and extensive margins. The base specification is structured as a difference-in-difference framework and takes the following form:

$$Y_{l,q} = \beta[\mathbb{L}_{l,q} \times \mathbb{P}_q] + \theta' \mathbf{\Theta}_{l,q-1} + \psi_l + \tau_q + \epsilon_{l,q}, \tag{9}$$

where $Y_{l,q} \in$ {*Quarterly CL Lending, Quarterly CL Origination Count, New Borrower CL Lending, New Borrower CL Origination Count*} for lender l in quarter q. $\mathbb{L}$ denotes bank–level conditioning and is one of *High Commitment* (taking value of 1 for banks in the highest tercile of undrawn commitments) or *Non-Regulated* (1 for DealScan lenders not impacted by LCR). $\mathbb{P}$ denotes the time indicator and is set in accordance with the transition phase of LCR, designed to capture the dosage effect of the liquidity regulation. The base indicator is *Post Regulation*, which is set to 1 for each quarter following 2017:Q1, which marks the full implementation of LCR. *Phase 1* takes a value of 1 for all four quarters of year 2015. Similarly, *Phase 2* and *Phase 3* are each assigned 1 for the four quarters of years 2016 and 2017, respectively. All time indicators are 0 for quarters preceding (and including) 2014:Q3. $\mathbf{\Theta}$ is the set of one–quarter lagged bank controls, as defined in Section 3.2.7. ψ denotes lender fixed effects and τ denotes quarter fixed effects.

I estimate the impact on credit line pricing employing a loan–level specification, to allow for the use of facility characteristics that affect pricing and to address borrower heterogeneity. In this estimations, I include controls for firm financial characteristics, loan features and risk-sharing in the specific syndication structure. Accordingly, these tests follow the specification:

$$Y_i = \beta[\mathbb{L}_{l,q} \times \mathbb{P}_q] + \theta' \mathbf{\Theta}_{l,q-1} + \omega' \mathbf{\Omega}_{f,q-1} + \lambda' \mathbf{\Lambda}_i + \psi_l + \tau_q + \epsilon_i, \tag{10}$$

where $Y_i \in$ {*Undrawn Spread, Drawn Spread, #Covenants, Initial Covenant Slack*} for loan (alternatively, package) i. $\mathbb{L}$, $\mathbb{P}$, $\mathbf{\Theta}$, ψ and τ are as before. $\mathbf{\Omega}$ is the set of lagged borrower controls and $\mathbf{\Lambda}$ denotes loan-specific controls, as defined in Section 3.2.7. Standard errors are dual-clustered by bank and quarter in both of the above specifications (Eq. (9) and Eq. (10)).

The next specification is for the set of tests investigating firm credit line borrowing on the intensive margin of borrowing firms. This is once again a difference-in-differences specification where the unit of observation is a borrower–quarter, and is given by:

$$Y_{f,q} = \beta[\mathbb{B}_{l,q} \times \mathbb{P}_q] + \omega'\mathbf{\Omega}_{f,q-1} + \iota_j \times \tau_q + \epsilon_{f,q}, \tag{11}$$

where $Y_{f,q} \in \{$*Quarterly CL Borrowing, Maturity, Drawn Spread, Undrawn Spread*$\}$ for borrower f in quarter q. $\mathbb{B}$ denotes borrower–level conditioning as defined in Section 3.2.6 and is either of *New Borrower*, or *Unconstrained Firm*. $\mathbb{P}$ and $\mathbf{\Omega}$ correspond to the definitions in Eq. (9) and (10). The interactive term $\iota_j \times \tau_q$ captures dynamic industry × quarter–fixed effects, for firm f in industry j. Standard errors are dual-clustered by industry and quarter.

Finally, I use a modified specification of Eq. (11) to estimate firm financial and real outcomes on the extensive margin. This specification takes the form:

$$Y_{f,t} = \beta[\mathbb{B}_{l,q} \times \mathbb{P}_t] + \omega'\mathbf{\Omega}_{f,t-1} + \phi_f + \iota_j \times \tau_q + \epsilon_{f,t}, \tag{12}$$

where, the outcome variables $Y_{f,t} \in \{$*Net Cash, Net Leverage, Cashflow Volatility, Asset Beta, Net Cash, Profitability, New Patents, R&D Expenses, Investment, Payout Ratio*$\}$ correspond to the borrower f in quarter (or year) t. The unit of observation is alternatively borrower–quarter or borrower–year, depending on the frequency of availability of the outcome variable. In this specification, I include firm–fixed effects through the use of ϕ_f. Standard errors are dual clustered by borrower and time (quarter/year, corresponding to the aggregation level).

5 Bank Lending Responses to LCR

5.1 LCR Exposure and Credit Line Origination

I begin by estimating Eq. (9) to gauge the differential impact of LCR on covered banks' credit line origination. The dependent variables are *Quarterly CL Lending*, and the alternate measure of CL origination, *Quarterly CL Origination Count*. The results are reported in Table 2.

TABLE 2 ABOUT HERE

The negative and statistically significant estimate in column (1) summarizes a key implication of LCR — banks facing the highest marginal cost of funding undrawn commitments cut back the most on their credit line origination.[14] The estimated coefficients are both statistically

[14] The uninteracted terms, *High Commitment* and *Post Regulation*, are subsumed by the bank– and quarter–fixed effects included in the specification.

and economically significant. The coefficient of –2.367 translates to a 52.11% decline for these highly committed banks over the pre-LCR mean (which was 4.542 for LCR-covered banks). In order to attribute these effects to the LCR, I estimate the impact around each implementation phase of LCR in columns (2) through (4). Credit line origination for highly exposed banks declined with each of the phases and coefficient estimates exhibit meaningful differences in terms of their economic magnitude. The magnitude of decline is lowest in column (2) following the implementation of Phase 1 of LCR, which set the compliance threshold at 80% (see Section 2). This translates to 12.11% (= −0.550/4.542) of the pre-LCR mean. This decline is amplified with subsequent phases — 28.23% and 36.42% following Phases 2 and 3, which set the compliance threshold to 90% and 100% respectively (columns (3) and (4)). I estimate the impact in terms of *Quarterly CL Origination Count* in columns (5) through (8), and find similar results. Column (5) shows that highly committed banks reduce their number of credit lines deals by 12.153% (= −0.206/1.695) of the pre-LCR mean of 1.695. The estimates corresponding to each phase of LCR, presented in columns (6) to (8) follow similarly "dosaged" declines in magnitude.[15]

I simultaneously analyze the impact of LCR on the spreads associated with new credit lines. To this end, I estimate the specification in Eq. (10) for covered banks categorized by *High Commitment*. Note that in this specification loans are categorized based on the lead arranger's treatment indicator. Table 3 reports the results of this estimation.

TABLE 3 ABOUT HERE

Columns (1) through (4) present the results on *Undrawn Spread* under a similar dosage treatment scheme as in Table 2. The results reveal that LCR had a heterogeneous impact corresponding to originating banks' exposure to LCR. Column (1) shows that the most exposed banks increased the undrawn spread the most and again, this increase carries statistic and economic significance. The pre-LCR mean *Undrawn Spread* for covered banks was 0.311. The estimate implies that the corresponding coefficient translates to a 35.7% (= 0.111/0.311) increase in economic terms. The effect magnitudes again increase in line with each phase of LCR: from 20.5% (= 0.064/0.311) in Phase 1 (column (2)) to 26.2% (= 0.089/0.311) in Phase 2 (column (3)) and 45% (= 0.139/0.311) in Phase 3 (column (4)). All of these effects are obtained controlling for the borrower's credit rating, loan characteristics and including a quarterly fixed effect, allaying concerns that the reported results are driven by credit worthiness or the macro interest rate environment.

[15] I provide evidence that these results are not driven by bank size by contrasting the differences between size and the level of undrawn credit line commitments in Appendix B. Further, Appendix Table C.1 shows that my results are robust to alternate cutoffs of undrawn commitments to assets in terms of above/below median, quartiles and quintiles, and as a continuous treatment variable.

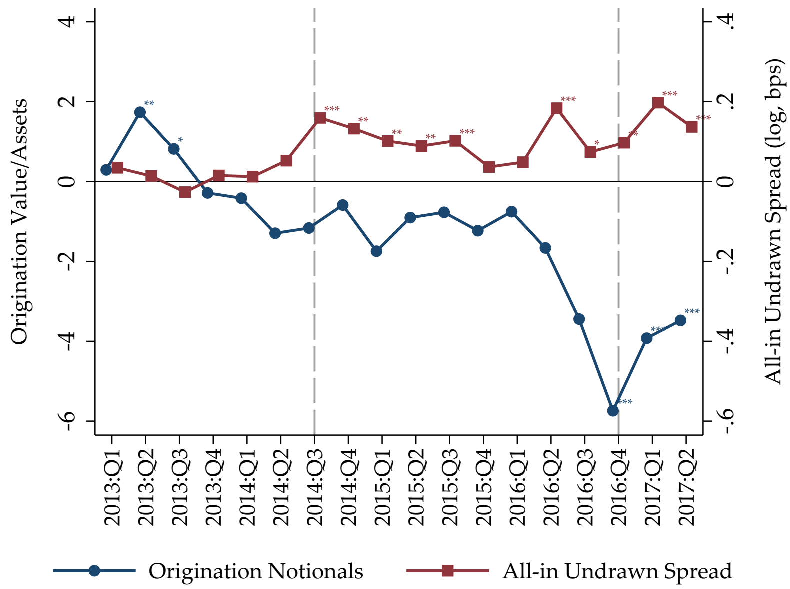


Figure 2. Quarterly Dynamics of Bank CL Lending. This figure depicts the quarterly variation in credit line origination by banks, conditioned on *High Commitment*. The blue (red) line represents coefficient estimates obtained from Eq. (9) (Eq. (10)) with the time treatment indicator replaced by a quarterly indicator. The dependent variable is *Quarterly CL Lending* (*Undrawn Spread*). The quarter–fixed effect (τ_q) is excluded in both specifications. Vertical lines indicate the quarters corresponding to LCR announcement (2014:Q3) and full implementation (2016:Q4). Statistical significance of coefficients is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Alongside, I show the results on *Drawn Spread* in columns (5) through (8). The dynamics in these columns follow analogous patterns as earlier albeit with far diminished economic magnitudes. The aggregate effect of LCR (column (1)) represents a 3.2% increase over the pre-LCR mean of 2.200 (= 0.071/2.200). The disparity in the effect magnitudes of *Drawn Spread* and *Undrawn Spread* suggests that the abnormal increase in undrawn spreads is unlikely to be driven by borrower credit characteristics. Berg et al. (2016) show using a sample of credit lines from the pre-LCR period (1986–2011) that borrower credit characteristics largely drive this difference, with higher drawn–undrawn disparity for borrowers less likely to draw on credit lines. My results are unlikely to be influenced by this dynamic, since I account for borrower credit characteristics with the set of borrower-specific control variables in my specification.[16] The abnormal increase in *Undrawn Spread* is therefore likely driven by the increased liquidity finding costs of banks most exposed to LCR.

I provide further perspective on the time variation of bank credit line lending in Figure 2 by means of coefficient plots estimated on variations of Eq. (9) and (10). The coefficient plot corresponding to *Quarterly CL Lending* as the dependent variable shows that banks with

[16]While I do show in later results that unconstrained firms *unconditionally* reduce their credit line borrowing, I do not find these results *conditional* on bank exposure to LCR.

high credit line commitments originated more credit lines than their low counterparts in the initial period (prior to LCR). The coefficient drops sharply and is statistically significant for all quarters following full implementation of LCR by the end of 2016:Q4. The plot corresponding to *Undrawn Spread* reveals that there were no differences between the two categories of banks prior to LCR. However, starting with Phase 1 of the regulation, highly committed banks begin to increase the undrawn spreads significantly more than their low counterparts. Notably, this price effect adjusts much earlier than the level effect denoted by *Quarterly CL Lending*.[17]

Together, the results in section reveal a sharp contraction in credit line origination, largely on the part of banks most impacted by LCR's asset holding requirements. LCR affects the spreads that impacted banks set on new credit lines, which increases firms' costs of maintaining corporate liquidity. In the subsequent sections I provide further evidence that attribute these effects to the advent of LCR and show important consequences to firms reliant on credit lines.

5.2 Non-Regulated Lending under LCR

In this section, I analyze broader implications of LCR by including a section of lenders that remain unimpacted by the regulation, or *Non-Regulated*. In doing so, I add to the insights gleaned in Section 5.1 in terms of both identification and economic implications. From an identification standpoint, this degenerate categorization generates further separation between the control and treated groups of lenders — *Non-Regulated* are outside the purview of LCR and not subject to costs of HQLA holdings. However, the rise in corporate liquidity's dependence on these lenders diminishes the policy effectiveness of LCR (see also Hanson et al. (2011)). I first present the results on origination levels, obtained under Eq. (9) in Table 4.

TABLE 4 ABOUT HERE

The results reveal a significant within–firm increase in credit line origination for non-regulated lenders in terms of both dollar volumes (columns (1) through (4)) and number of deals (columns (5) through (8)). The pre-LCR mean for this sample of lenders was 1.636. The coefficient of 1.048 in column (1) therefore implies a 64.29% within–firm increase in quarterly credit line origination. Once again, the economic magnitudes increase in line with LCR's transitory compliance thresholds. I find analogous results for the alternate measure of *Quarterly CL Origination Count*, with a 6.25% ($= 0.106/1.695$) quarterly increase (column (5)).

I next complement these origination results with an analysis of the pricing impacts by *Non-Regulated* lenders. The corresponding results are obtained from an estimation of Eq. (10) and reported in Table 5.

[17] I present additional evidence on the cross-sectional relationship between undrawn commitments and *Quarterly CL Lending* in Appendix Figure C.1.

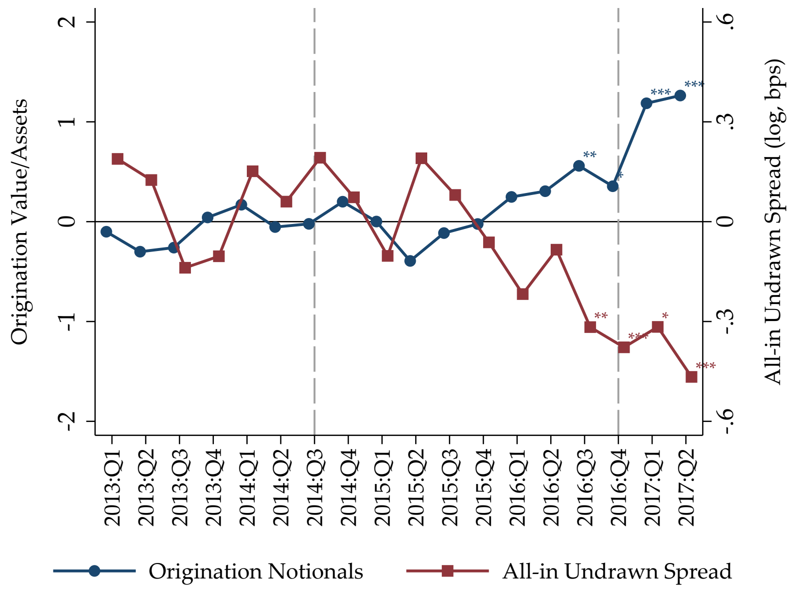


Figure 3. Quarterly Dynamics of Non-Regulated Lending. This figure depicts the quarterly variation in credit line origination by banks, conditioned on *Non-Regulated*. The blue (red) line represents coefficient estimates obtained from Eq. (9) (Eq. (10)) with the time treatment indicator replaced by a quarterly indicator. The dependent variable is *Quarterly CL Lending* (*Undrawn Spread*). The quarter–fixed effect (τ_q) is excluded in both specifications. Vertical lines indicate the quarters corresponding to LCR announcement (2014:Q3) and full implementation (2016:Q4). Statistical significance of coefficients is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

TABLE 5 ABOUT HERE

I find that *Non-Regulated* lenders set lower spreads, in terms of both *Undrawn Spread* (columns (1) to (4)) and *Drawn Spread* (columns (5) to (8)). The benefits of non-regulated lending has been attributed to convenience and lower screening in the literature, rather than costs. The fact that they set lower spreads is unique to the setting of corporate credit lines (e.g., Buchak et al. (2018) report comparable interest rates for regulated and non-regulated lenders in mortgage markets, and lower marginal funding costs for regular banks) and is attributable to higher liquidity funding cost incurred by LCR-regulated banks in maintaining undrawn credit lines.

I provide an analysis of parallel trends between regulated and non-regulated lenders in Figure 3. The figure reveals no significant differences in terms of origination or prices between the two categories of lenders in the initial period prior to LCR. The differences start to become salient during the transitory period and are prominent with full implementation of LCR, with statistically significant coefficient estimates.

6 Evolution of Bank–Borrower Relationships

The heterogeneous credit line declines among lenders spurred by LCR signals uneven credit line lending to the borrower base of these banks. Borrowers, especially small firms, depend on bank relationships to fund corporate liquidity requirements (e.g., Petersen and Rajan (1994), Degryse and Ongena (2005), and Bharath et al. (2011)). In the next set of tests, I gauge the ability of firms to form new banking relationships in the post-regulation lending environment in accordance with bank exposure to LCR. To do so, I single out lending to new borrowers using *New Borrower*, which is the total lending by each bank to firms with whom they did not have a prior relationship, as the dependent variable in Eq. (9). Table 6 reports the results.

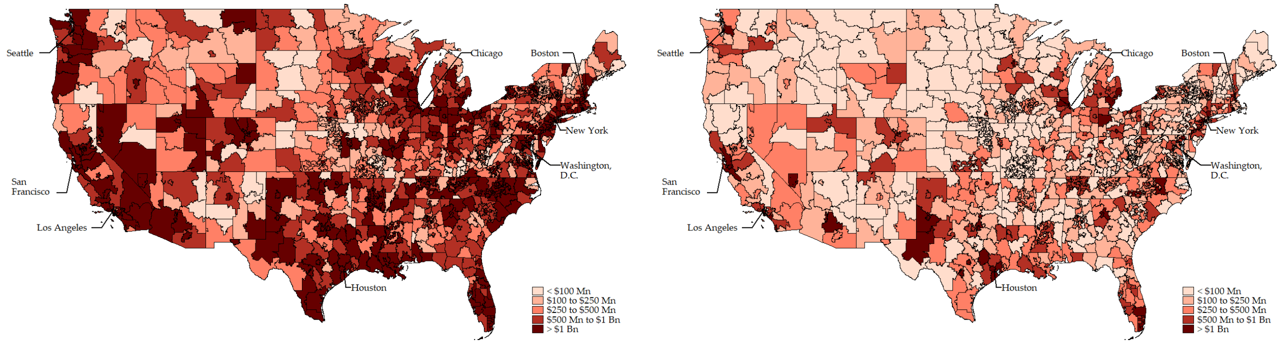
TABLE 6 ABOUT HERE

The negative and significant coefficients in columns (1) through (4) indicate that greater exposure to LCR is associated with lower credit line lending, in terms of origination amounts, to new borrowers. The coefficient in column (1) places the economic magnitude of this decline at 67.6% of the pre-LCR mean of 0.988 ($= -0.668/0.988$). It appears that banks are unable to pass on their increased costs of maintaining liquidity, since they do not hold bargaining power against these new borrowers. Columns (5) through (8) show that with increasing LCR exposure banks also engage in a fewer number of deals with new borrowers, indicating that LCR-implied funding costs constrain banks' ability to establish new lending relationships.

In the vein of lending relationships, I also establish the channel through which non-regulated lenders increase their credit line origination. This could occur either through (1) increasing lending to existing borrowers; or (2) expanding their lending network forming new lending relationships. The latter implies that an increasing *number* of firms rely on the non-regulated channel to meet their liquidity requirements, which would severely diminish the intended effects of the LCR rule, which was to create a liquid financial intermediary system. My next empirical result addresses this tension and is estimated using Eq. (9) with lenders conditioned on *Non-Regulated*. These results are reported in Table 7

TABLE 7 ABOUT HERE

Non-regulated banks increase lending to new borrowers in the post-regulation period. This increase prevails in terms of credit line values (columns (1) through (4)) and number of new deals (columns (5) through (8)). The associated economic magnitudes are large — non-regulated lenders increase their total credit line lending to new borrowers by 49.9% of the pre-LCR mean of 0.765 (column (1)), and also originate 10.6%($= 0.168/1.589$) more deals



(A) Regulated Lenders **(B)** Non-Regulated Lenders

Figure 4. Geographical Dispersion of Credit Line Lending. This figure presents the access of firm–establishments to credit line borrowing from regulated banks (Panel A) and non-regulated lenders (Panel B) in the pre-LCR period. In each of these panels, the metric of an establishment's exposure to credit lines is determined as the product of total credit line borrowed by the firm, respectively from regulated and non-regulated lenders, and the ratio of establishment–level employees to total firm employees (based on one-year lagged YTS employee data). This metric is then aggregated at the 3-digit ZIP–level, and average across all quarters in the pre-LCR period (2013:Q1 through 2014:Q3).

towards new borrowers (column(4)). These results show that with the advent of LCR, an increasing *number* of firms rely on non-regulated lenders for their corporate liquidity. Consequently, these firms remain exposed to liquidity crises unlike firms borrowing from regulated banks, who are covered by LCR and provide assurance of liquidity supply during crises. In the following section, I compare and contrast the geographical proliferation of these lending relationships.

6.1 Geographical Dispersion of Credit Line Lending

The transfer of liquidity creation from the regulated to the non-regulated banking system has important consequences not only during liquidity crises. As I show in this section, there are fundamental differences in lending patterns of these banks that constrain liquidity even in normal times. I present a novel analysis of firm–establishments' access to credit lines by extending my base panel to capture this geographical dispersion to include establishment–level data from YTS. With this extended panel, I calculate average the establishment–level access to credit lines over the pre-LCR quarters of 2013:Q1 to 2014:Q3, aggregating at the 3-digit ZIP code corresponding to the establishment's location.[18] Figure 4 depicts the map of this average establishment–level credit line exposure.

[18]For a given firm–establishment, I calculate the access to credit line using an employment weighted-scheme as $\textit{CL Access}_{i,q}^{\textit{Non-Regulated}} = \textit{Quarterly CL Borrowing}_{q}^{\textit{Non-Regulated}} \times \frac{\mathbb{E}_{i,y-1}}{\sum_{j\in\mathbb{J}}\mathbb{E}_{j,y-1}}$, where $\mathbb{E}_{i,q}$ denotes the employment level of establishment i within the set of firm–establishments $\mathbb{J}$ in lagged year $y-1$ corresponding to quarter q. *Non-Regulated* is a categorical variable taking the value of 1 for non-regulated lenders.

The distribution in Panel A shows that liquidity generated by regulated banks flows through to many regions of the country, with the largest cities of most states exhibiting high access to credit lines by way of their parent firm. Regions experiencing lowest levels of access comprise rural and exurban areas of U.S. These observed patterns are consistent with regulated banks lending to large and dispersed firms. Moreover, these banks rely primarily on liquidity conversion of deposits and this can occur at the branch– or regional–level enabling borrowing even by firms concentrated around smaller financial centers.

Panel B depicts a striking contrast in corporate liquidity generated by non-regulated lenders. The regions with highest levels of access to credit lines in this case are concentrated around major financial centers with the metric of credit line access dropping rapidly moving away from these regions. These patterns reveal fundamental differences in the borrower selection process between regulated and non-regulated lenders. Non-regulated lenders appear to provide credit predominantly to smaller, less-dispersed borrowers with "lean" operations. The concentrated lending pattern is also a fallout out of these lenders' markedly different liquidity conversion processes. They rely on market-funded short term debt to finance outflows, which in turn is raised from informed and concentrated lenders (Jiang et al. (2020)). This is reflected in their lending preferences with a particular affinity to large financial centers.[19]

The geographical heterogeneity in lending patterns has important consequences to corporate liquidity creation following the shift to non-regulated borrowing. In Figure 5, I present the post-LCR changes in credit line access under the same ZIP code–level mapping scheme. The map reveals highest declines in interior regions of U.S., away from the main financial centers, amounting to as high as 100%. This includes parts of Arkansas, Colorado, Maine, Minnesota, Montana, New Mexico, and New Hampshire, among others. I statistically reject the null of spatial randomization (with $p < 0.001$) based on Moran's I test statistics, which reveals clustered patterns in these declines. A comparison with Figure 4 shows that most pronounced cuts occur in regions with low non-regulated lending exposure. The implication of this result is that non-regulated lenders do not completely close the corporate liquidity gap created by banks' cutbacks on credit line origination. Regions in the interior of the country, especially, face a dramatic shortfall of intermediated corporate liquidity. This is all the more worrying considering that firms in these regions are also constrained in their access to major capital markets. In the next section, I present another dimension of *normal* time differences in terms of contractual strictness through the use of covenants.

[19]See also Appendix E for an analysis in terms of borrowers' headquarters location. Non-regulated credit line lending diminishes rapidly for borrowers with HQ located more than 150 miles from major economic centers.

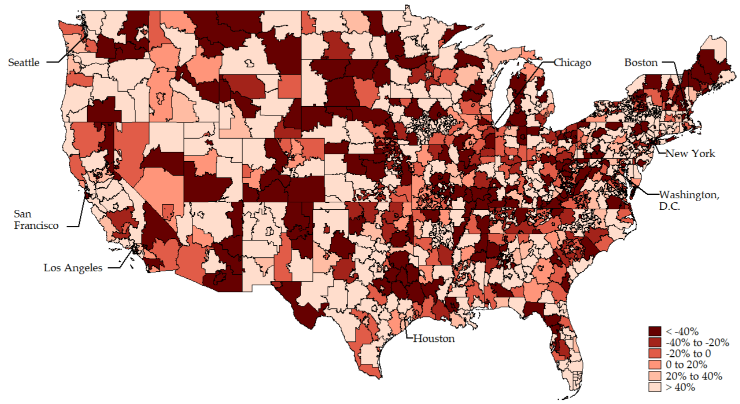


Figure 5. Post-LCR Changes to Establishment Credit Line Access. This figure depicts the change in credit line access, at the firm–establishment level, following full implementation of LCR at the end of 2016:Q4. Establishment's credit line access is the employment-weighted share of the parent firm's within–quarter borrowing. This measure is aggregated across all establishments within the same 3-digit ZIP code, as in Figure 4. Change in credit line access is calculated as post-LCR access (averaged across 2017:Q1 to 2018:Q2) minus pre-LCR access (averaged across 2013:Q1 to 2014:Q3), divided by pre-LCR access.

6.2 Strictness of Credit Line Lending

The next outcome I consider is the level of control banks exercise on their credit line borrowers, through the monitoring channel. I proxy for this using a number of measures defined on credit line covenants and collateral underlying the loan. Supply-side constraints play a key role in determining the usage and thresholds of covenants (Murfin (2012)), with credit lines following dynamics different from term loans (Berlin et al. (2020)). I investigate the impact of LCR on credit line covenants in columns (1) through (6) of Table 8.

TABLE 8 ABOUT HERE

The results reveal important differences in the usage of covenants depending on bank-level exposure to LCR. Conditional on the deal carrying a covenant, high credit-line–committed banks tend to include more covenants (column (1)), whereas non-regulated lenders tend to include fewer covenants (column (2)). The pre-LCR mean of *#Covenants*, was 0.97 or 1.64 ($= e^{0.97} - 1$) covenants per package. The coefficient of 0.205 in column (1) points to number of covenants increasing by .23 ($=e^{0.205} - 1$), on average, for banks with high undrawn commitments. For non-regulated banks, the number of covenants correspondingly decreases by 0.50 ($= e^{-0.428}$-1). Unconditionally non-regulated lenders have a higher tendency to include at least one covenant relative to regulated banks (column (6)), which is attributable to the difference in their funding structures (Buchak et al. (2018)). However, column (4) shows that non-regulated lenders set covenant thresholds farther from the level of the corresponding ratio at origination, indicating that these lenders incur higher costs of monitoring. Finally, columns

(7) and (8) show that both non-regulated and highly exposed banks increasingly originate secured credit lines, a fact that makes the overall credit line market less attractive to borrowing firms (e.g., Campello et al. (2021a) show that firms prefer unsecured borrowing, even when their pledgeable assets appreciate in value).

7 Textual Analysis of Credit Line Contracts

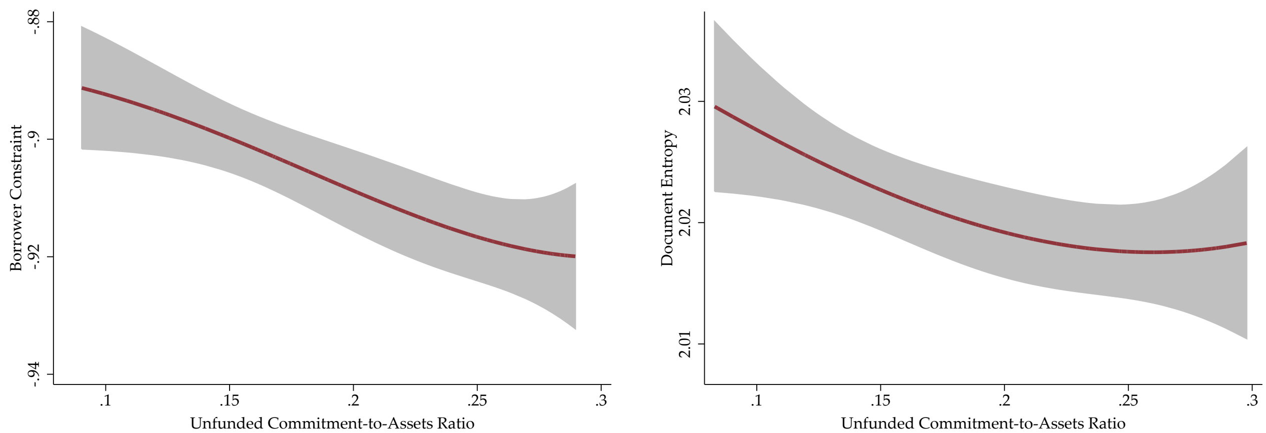
I now analyze the soft information contained in credit line agreements that I obtain by scraping SEC filings of borrowers. With these contracts, I use a number of measures drawn from machine learning tools to analyze important features of the agreement. The measures broadly capture the bank's risk aversion and its bargaining power in a given credit line transaction. To this end, I construct the variables *Borrower Constraints*, *Early Termination Clause*, *Seniority Clause*, and *Contracting Complexity* as described in Section 3.2.4. I use them as dependent variables in Eq. (9). The results are reported in Table 9.

TABLE 9 ABOUT HERE

The first metric that I consider is *Borrower Constraints*, which is a measure of the relative bargaining power of the bank as compared to the borrower. I construct this measure this by calculating the number of constraining clauses pertaining to the borrower relative to those in the document as a whole. The positive and significant coefficient in column (1) signifies that banks more exposed to LCR increased the contractual constraints that they impose on the borrower, relative to less exposed banks. This result supports my earlier result that banks seek to pass on the increased costs of maintaining liquidity on to its credit line borrowers. They achieve this, at least partly, by lending mainly to borrowers with whom they hold significant bargaining power. For these borrowers, highly committed banks can charge higher spreads on undrawn credit line commitments.

The next two metrics measure banks' usage of contractual safeguards by means of the right to call the credit lines and seniority of payments. The positive and significant coefficients in columns (2) and (3) show that higher LCR exposure leads to greater usage of early termination and seniority clauses in credit line agreements. With the advent of LCR, banks incur higher costs in originating and maintaining credit lines. The results show that banks seek to offset their losses in the case of a liquidity shock to the borrower. The increased usage of these clauses also implies that banks have legal recourse to payments that would prevent shocks from being transmitted across the financial system.

The last measure is *Contracting Complexity*, which signifies the information contained per word of the document (or, *local entropy*). Higher entropy translates to lower information



(A) Borrower Constraints

(B) Document Complexity

Figure 6. Pre-LCR Bank Credit Line Holdings and Contracting Terms. This figure plots the cross-sectional relationship between the contracting term metrics and total undrawn commitments held by the lending bank, in the pre-LCR period (2013:Q1 to 2014:Q3). Panel A (B) shows the fractional-polynomial regression fit of *Borrower Constraints* (*Contracting Complexity*) on the bank's total undrawn commitments, scaled by assets. The shaded regions represent 95% confidence interval.

conveyed per word and denotes the usage of complex and verbose legal language (see Section 3.2.4). The positive and significant coefficient in column (4) indicates higher document complexity for credit lines originated by highly committed banks, relative to their low counterparts. This result shows that exposed lenders create more customized agreements on a case-by-case basis, as opposed to employing "boilerplate" contracts.

I next characterize the textual dependent variables to bank credit line exposure in the pre-LCR period. Figure 6 depicts the cross-sectional relationship between *Borrower Constraints* and *Contracting Complexity*, respectively, against the originating bank's total undrawn credit lines. Both plots reveal a strong, negative correlation in the pre-LCR period. This negative association implies that the results reported in Table 9 are not artefacts of the variable's construction but are profound implications that LCR had on credit line contracting terms. The negative correlation in the pre-LCR period can be attributed to the fact that these banks sought to expand their credit line origination by imposing fewer restrictions on borrowers. In the absence of LCR-mandated liquidity buffers, undrawn credit line spreads constitute a major source of income to banks, associated with little counterparty insolvency risks.

8 Composition of Post-LCR Borrowers

Understanding the real consequences of regulating liquidity, requires that the aggregate contraction in credit line lending be distinguished into bank-driven liquidity-rationing *vs.* firm-

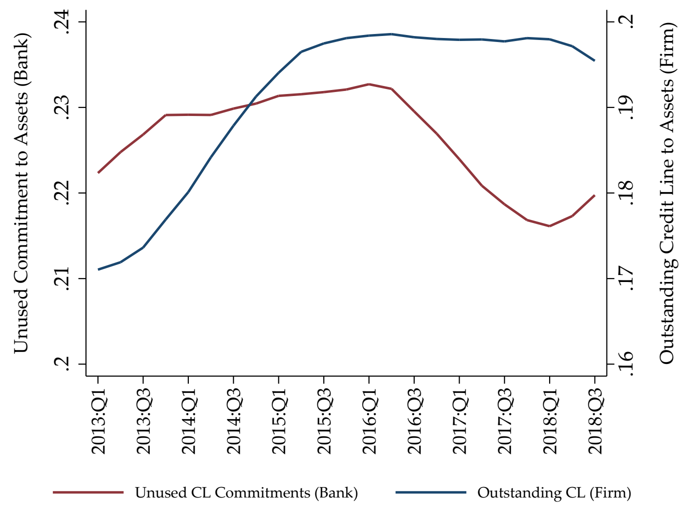


Figure 7. Credit Lines and Firm Size. This figure plots the four-quarter rolling average of undrawn credit line commitments, averaged across all banks (in red) and the total outstanding credit line borrowing by firms calculated from DealScan, averaged across all borrowing firms in the sample (in blue) between 2012:Q1 and 2018:Q3. Both series are presented as a fraction of total assets.

driven choice towards alternate liquidity policies. Liquidity rationing would imply a break down in the mechanism of financial intermediation, whereas altered firm liquidity policies indicate a push towards disintermediation of liquidity with less deleterious system-wide consequences. In the subsequent set of tests focusing on borrowers of syndicated credit lines, I aim to establish this distinction. I first provide a perspective on the economic magnitudes associated with the new development in the form of the LCR regulation. Figure 7 depicts the average of total outstanding credit line notionals as a fraction of banks' and borrowing firms' total assets over the sample period. Undrawn credit line commitments represent up to 23% of the average bank's total assets, which rationalizes the large opportunity costs incurred by banks in funding the liquidity coverage, on top of the capital adequacy requirements. For firms, total outstanding credit lines represent between 17% and 20% of assets.[20] In terms of revenues, a 10 basis point increase in undrawn spreads translates to 0.2 cents of additional expenses, per dollar of revenue. Firms are thus expected to significantly alter their liquidity policies in response to this economically significant rise in the cost of maintaining credit lines, combined with tighter monitoring.

In this section, I investigate firm borrowing responses to the changes in the pricing, origination and strictness of credit line lending. The results in previous sections show that the aggregate borrowing is shifting to the non-regulated system, which poses the problem of liquidity running dry when it is most required. Unlike regulated banks, these lenders are not required to maintain liquidity buffers against system-wide shocks. On the other hand, regulated banks would be wary

[20] These levels are consistent with other statistics reported in the literature (e.g., Acharya and Steffen (2020)).

of increasing their exposure to credit line obligations as this would mean that they incur significant opportunity costs to their asset base, and in turn pass on these costs to their borrowers.

In my first set of tests, I analyze the aggregate impact on new borrowers entering the syndicated credit line market. With lenders becoming more selective in their screening of borrowers, such firms face the greatest barriers in raising intermediated corporate liquidity. The results reported in Table 10 assert this fact.

TABLE 10 ABOUT HERE

Column (1) shows that credit lines to new borrowers decline 36% (= 0.083/0.230) compared to matched within–industry new borrowers in the pre-LCR period (the matched sample mean of 0.230). They are also locked in for higher commitment periods (column (3)) and face higher costs in terms of both undrawn and drawn spreads (columns (3) and (4)). This result also provides further clarity to the results reported in Section 6, which showed that non-regulated lenders form new lending relationships in the post-LCR period. The fact that new borrowers decline in aggregate, in conjunction with their higher borrowing costs, suggests that non-regulated lenders are tapping into a portion of regulated banks' market, as opposed to bringing new borrowers into the fold.

I next analyze the overall composition of borrowers reliant on the syndicated lending market for their corporate liquidity needs. With the implementation of LCR, banks are more constrained in terms of originating credit lines. Under these constraints, banks would unconditionally prefer lending to safer and unconstrained borrowers. From a firm-side perspective the same tightening would imply that unconstrained firms, who have access to other sources of corporate liquidity, would reduce their dependence the most. In my next set of tests, I attempt to resolve this dichotomy and in doing so attribute the aggregate lending decline (Figure 1) to either of (1) bank liquidity-rationing, or (2) changing firm liquidity policies. Accordingly, in these tests, I condition firms on the intensive margin of borrowers, based on their constraint in accessing capital (following the Size-Age Index of Hadlock and Pierce (2010)). The results are reported in Table 11.[21]

TABLE 11 ABOUT HERE

Columns (1) through (4) show that *unconstrained* borrowers reduce their credit line borrowings the most. The estimate of –0.272 in column (1) translates to a 36.6% reduction in quarterly credit line borrowings, from the pre-LCR mean of 0.742, for unconstrained firms compared to their constrained counterparts. In columns (2) to (4), I show the phase-wise impact on

[21] In Appendix Table C.3, I validate the results under alternative classifications of financing constraints including terciles of size, whether the issuer has a credit rating and if so, whether it is investment grade.

the borrowing of such firms, and the gap widens with each successive implementation phase. These results carry an important economic implication. They show that following LCR, the capital market divide between firms based on their financing constraints has widened further — smaller and younger firms rely on intermediaries to meet their liquidity needs to an increased extent. This even more salient given the aggregate tightening in lending terms imposed by intermediaries. Columns (5) to (8) show that the costs incurred by *unconstrained* firms increased in relative terms, again in line with the implementation phases of LCR. I attribute this to the fact that the residual unconstrained borrowers in the syndicated lending market face increased default risks, a dimension that is not fully captured in the SA index (e.g., Acharya et al. (2012) show that cash holdings are correlated with default, for all categories of SA index). I show this formally as part of my tests in the following section, where I introduce secondary conditioning in terms of borrower characteristics.

8.1 Drivers of Firm Credit Line Borrowing

In this section, I investigate heterogeneity in firm borrowing responses to LCR by conditioning on a number of financial measures that correspond to firms' appetite for credit lines. Specifically, I rank firms based on terciles of the secondary conditioning variables, *Debt Due in 1 Year*, *Tangibility*, *Innovation*, and *Default Probability* and categorize them to *Low* and *High* terciles. I then estimate Eq. (11) on these conditioned samples. The results are reported in Table 12.

TABLE 12 ABOUT HERE

Columns (1) and (2) describe the differential firm credit line borrowing responses depending on the current portion of their long term debt. Firms with highest levels on long term debt due within the next year, face the *relatively* highest need to refinance or retire their debt. This provides an important juncture at which firms can alter their financial and liquidity policy when faced with higher costs and monitoring in credit lines. The coefficient in column (1) carries no statistical or economic significance, whereas that is column (2) is negative and significant. Together, these show that the decline in unconstrained firm borrowing is driven to a large extent by those with the highest need to refinance existing debt.

The next two columns, (3) and (4) show that the decline is driven by firms with low *Tangibility*. There is a marked decline in credit line borrowing by unconstrained firms with low tangibility (column (3)), whereas firms with high tangibility exhibit no perceptible differences in their borrowing (column (4)). This pattern is consistent with the increase in secured lending, with low pledgeability driving firms' borrowing choices. In the spirit of pledgebaility, I categorize firms into terciles of knowledge capital-based Total Q (Peters and Taylor (2017)) in columns (5) and (6).

The results reveal that highly innovative and unconstrained firms reduce their credit line borrowing the most. This can be attributed to the fact that their innovation capital is valued higher by equity investors rather than as debt collateral (Brown et al. (2009); Kerr and Nanda (2015)).

Finally, the estimates in columns (7) and (8) are obtained by partitioning the sample on the borrower's expected default. The negative and significant coefficient in column (7) suggests that unconstrained borrowers with low default risk largely drive the declines. On the other hand, there are no significant differences in high default risk firms (column (8)). This last result indicates that unconstrained borrowers remaining in the market for credit lines, in aggregate, carry higher default risks. These firms rely most on bank financing to meet their corporate liquidity needs and continue to borrow via credit lines despite the higher costs and monitoring levels.

9 Corporate Liquidity Policy, Risk, and Real Outcomes

In my next set of results, I analyze the continued importance of credit lines to firms in the post-LCR liquidity regime. The results in previous section reveal an exodus of firms away from credit line borrowing towards alternate forms of liquidity. A shift in firms' liquidity policy on the back of less favorable credit line terms has important downstream consequences to firms, amplifying the effects of increased costs themselves. I first investigate the impact on firms' cash holdings, stability of cashflows and overall financial stability. I use them as dependent variables in an extensive margin analysis, described by Eq. (12), and report the results in Table 13.

TABLE 13 ABOUT HERE

I show the baseline comparison with cash holdings, which are complementary liquidity claims (e.g., Acharya et al. (2013)), in column (1). The statistically significant coefficient estimate of 0.066 in column (1) denotes that firms look to cash as an alternative form of corporate liquidity, more than doubling their net cash holdings from the pre-LCR mean of 7.5% of assets. Next, column (2) shows that these firms finance this increased cash holding through debt, reflected in their higher financial leverage.[22] The financial leverage for switching firms increases by 4.8% (= 0.009/0.186) in the post-LCR period. The next two columns show that the shift in liquidity policy, combined with an increase in financial leverage, leaves these firms more susceptible to macroeconomic conditions than firms that continue to borrow credit lines. Following an exit from credit line borrowing, firms' cashflow volatility increases by 8.52%, as denoted by the column (4) coefficient of 0.132 (the pre-LCR mean of *Cashflow Volatility* was 1.549). This is also accompanied by a statistically significant increase in their asset betas (column (5)).

[22] Firms raising cash through debt, rather than equity, is consistent with *leverage ratchet* (Admati et al. (2018)).

Lastly, I find that firms' default risks increase as they substitute costly and tightly monitored credit lines with debt-financed cash holdings. This result is depicted in column (6) which translates to a 50.7% higher default probability for firms seeking alternate liquidity channels. This result shows that firm managers exhibit increased risk-seeking behavior in the absence of tight monitoring controls imposed by credit line lenders. While the higher default risk is partly an artefact of these firms' increased leverage, another contributing factor is the lower level of monitoring embedded in debt as opposed to credit lines. This last observation follows from the results reported by Berlin et al. (2020), who show an aggregate decline in monitoring levels of term loans for a similar time period. Together, the above results highlight the importance of credit lines in modulating firms' aggregate risk characteristics and macroeconomic exposure.

The last set of results in this paper investigate the role played by credit line-based liquidity in firms' real outcomes including profitability, innovation, and payouts. Credit lines provide low-cost liquidity to firms, freeing up cash holdings for investment. With the implementation of LCR, however, credit lines have turned costlier. In the next set of results, I provide evidence that firms' alternate forms of liquidity appear to have beneficial consequences to firm performance. These are reported in Table 14.

TABLE 14 ABOUT HERE

Note that columns (1) through (3) correspond to borrower–quarter observations, whereas columns (4) through (6) correspond to borrower–year observations, corresponding to the outcome variable's reporting frequency. Column (1) shows that firms opting out of syndicated credit line borrowing show higher profitability, compared to firms that opt to continue their credit line borrowings. This is also partly attributable to the fact that they are mostly comprised of unconstrained firms. These firms also appear to be more innovative with higher number of patent filings (column (2)), increased R&D spending (column (3)), and capital investments (column (4)). Together, they indicate the role played by banks in financing innovation diminishes further with LCR-imposed liquidity constraints (e.g., Brown et al. (2009) show that young and innovative firms preferred equity funding even prior to the implementation of LCR). Additionally, they reinforce the idea that increased cash reserves are financed through debt issuance, rather than through cash from operations (the latter would entail a decrease in investments). Finally, the coefficient in column (5) indicates an increase in shareholder payout through dividends and repurchases. With lowered monitoring, firm managers appear to engage in riskier policies suggesting a wealth transfer from debtholders to equity holders. The results warn of long-term consequences of firms' alternative liquidity policies in response to LCR-induced credit line declines.

10 Concluding Remarks

In this paper, I study the downstream implications of regulating bank liquidity as part of the Basel III guidelines, focusing particularly on the liquidity coverage ratio rule (LCR). I present evidence that banks have significantly altered their origination of credit lines, as a consequence of the higher cost of maintaining liquid assets in order to honor drawdowns. Conditioning banks on levels of their exposure to LCR, I show that highly exposed banks increase credit line spreads and monitoring levels. Using novel textual metrics of contractual strictness, I show that highly exposed banks also increase the constraints they impose on borrowing firms. The collective changes induced in the syndicated lending market have made credit lines less favorable as sources of corporate liquidity to firms and in turn, diminished banks' credit line origination.

A natural consequence of banks reducing their credit line origination is the rise of non-regulated lenders, who originate a greater share of credit lines following LCR's implementation. However, they exhibit greater selectivity in terms of borrowers and geographies and do not uniformly offset declines in credit line lending by banks. More importantly, these non-regulated lenders are largely left uncovered by the post-Financial Crisis regulatory reforms. An increasing number of corporations, especially the most constrained, relying on the non-regulated system for liquidity signals a deviation from the intended consequences of the regulatory policy. This is further compounded by the fact that unconstrained firms appear to meet their liquidity demand through cash financed primarily through debt issuance, moving away from credit lines altogether. This change in firms' liquidity policies has implications to their risk profiles, rendering them riskier in aggregate. While such firms do exhibit enhanced performance in the short term, much of their wealth appears to be transferred to equity holders by way of increased payouts. An unintended consequence of regulating banks' liquidity positions seems to be that large and unconstrained firms, and their debtholders, adopt riskier corporate liquidity policies and are increasingly exposed to stock market pressures.

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Table 1. Descriptive Statistics

This table presents descriptive statistics for the main variables used in my empirical analyses over the 2013:Q1–2018:Q2 period. The unit of observation is alternately bank–quarter, borrower–quarter, loan or deal package. *Quarterly CL Lending* is the sum of notional amounts of dollar denominated credit line lending by a given bank in a given quarter, scaled by total bank assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated by a given bank in a given quarter. *Undrawn Spread* is the logarithm of one plus the all-in undrawn spread over the base rate associated with the credit line facility. *Drawn Spread* is the logarithm of one plus the all-in drawn spread over the base rate associated with the credit line facility. *New Borrower CL Lending* is the sum of notional amounts of dollar denominated credit line lending to firms that borrowed from the given bank for the first time in the given quarter, scaled by industry average of total assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated towards firms that borrowed from the given lender for the first time in the given quarter. *#Covenants* is the logarithm of one plus the average number of covenants (both financial and net worth covenants) included in each package originated by the lender in the quarter. *Initial Covenant Slack* is the distance between the covenant threshold and its level at origination, scaled by the initial level and averaged across all deals originated by the lender in a quarter. $\mathbb{1}$*(Covenants)* is an indicator variable that takes the value 1 for deals that include at least one covenant, and 0 for deals which have no covenants attached. $\mathbb{1}$*(Secured)* is an indicator variable that takes the value of 1 for each credit line deal that is secured by collateral, and 0 otherwise. *Borrower Constraints* the logarithm of one plus the number of constraining sentences in a credit line agreement pertaining to the borrower, divided by the total number of constraining sentences in the agreement. *Early Termination Clause* is the maximum of the pairwise cosine similarity between phrases in the document and a pre-determined sample early termination clauses. *Seniority Clause* is the maximum of the pairwise cosine similarity between phrases in the document and a pre-determined sample early termination clauses. *Contracting Complexity* is the mean of the distribution of linguistic entropy (Shannon (1951)) of each word in the document. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *Maturity*, is the logarithm of one plus the weighted average maturity of credit lines borrowed by a given firm in a given quarter. *Net Cash* is cash and short-term investments net of current liabilities, scaled by total assets. *Net Leverage* is the total short- and long-term debt net of cash divided by total assets. *Cashflow Volatility* is constructed following Minton and Schrand (1999) as the coefficient of variation in the quarterly operating cashflow, over the preceeding 24 quarters (six years). *Asset Beta* is calculated by unlevering quarterly stock market beta, estimated using CAPM. *Default Probability* is the physical probability of default corresponding to Bharath and Shumway (2008), on the last day of the preceding quarter. *Profitability* is net income divided by lagged total assets. *New Patents* is one plus the logarithm of number of patent applications by the firm in the quarter. *R&D Expenses* is quarterly research and development expenses scaled by total assets. *Investment* is capital expenditures divided by total assets. *Employees* is the sum of employees of all firm-establishment for the year, scaled by lagged total assets. *Establishments* is the number of firm establishments, scaled by total firm employees. The unit of observation is a firm–quarter in columns (1) to (3) and firm –year in columns (4) to (6). *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Non-Regulated* is an indicator variable that takes the value of 0 for lenders in the Thomson-Reuters' LPC DealScan sample that report FR Y-9C data and 1 for the rest. *New Borrower* is an indicator variable that takes the value of 1 for firms borrowing syndicated credit lines for the first time in a given quarter, and 0 for returning borrowers matched on age, size, Q, profitability, net financial leverage, and net worth. *Unconstrained Firm* is an indicator variable that takes the value of 1 for firms in the lowest tercile of the size-age index (Hadlock and Pierce (2010)), and 0 for firms in the highest tercile. *Non-Borrower* is an indicator variable that takes the value of 1 for a firm that exits the syndicated lending market for credit lines following full implementation of LCR on January 1st, 2017, and did not borrow for three years preceding this date. The variable takes the value 0 for firms that continue to borrow syndicated credit lines following this period. Bank controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth.

Variable	N	Mean	SD	Median	IQR
		Dependent Variables			
Bank Lending					
Quarterly CL Lending (per $1000 assets)	4,916	1.49	3.56	0.36	1.25
Quarterly CL Origination Count (log)	10,844	1.73	0.97	1.10	0.98
Undrawn Spread (100·log)	27,378	0.34	0.16	0.35	1.00
Drawn Spread (100·log)	27,378	2.21	1.15	1.73	1.71
New Borrower CL Lending	10,844	0.63	1.50	0.08	0.62
New Borrower Loan Origination Count	10,844	2.55	1.33	2.39	2.11
Covenant Characteristics					
#Covenants	14,892	0.97	0.29	1.10	0.40
Initial Covenant Slack	2,763	0.19	0.13	0.16	0.14
$\mathbb{1}$*(Covenants)*	49,695	0.29	0.45	0.00	1.00
$\mathbb{1}$*(Secured)*	49,695	0.40	0.49	0.00	1.00
Contract Textual Variables					
Borrower Constraints	2,562	–0.91	0.10	–0.91	0.10
Early Termination Clause	2,562	0.59	0.04	0.59	0.05
Seniority Clause	2,562	0.64	0.03	0.64	0.04
Contracting Complexity	2,562	2.01	0.03	2.02	0.04
Firm Credit Line Borrowing					
Quarterly CL Borrowing	5,880	0.32	3.75	0.14	0.21
Maturity(log)	5,880	4.34	1.28	5.00	1.00
Firm Risk and Real Outcomes					
Net Cash	59,827	0.07	0.15	0.04	0.12
Net Leverage	59,827	0.20	0.29	0.21	0.38
Cashflow Volatility	59,827	1.50	2.02	0.93	0.98
Asset Beta	59,827	0.99	0.58	0.92	0.62
Default Probability (×100)	59,827	2.01	9.76	0.00	0.33
Profitability	59,827	0.01	0.05	0.01	0.02
New Patents	59,827	0.26	0.76	0.00	0.00
R&D Expenses	59,827	11.63	19.32	5.18	15.36
Investment (Annual)	10,773	0.08	0.13	0.05	0.07
Payout Ratio (Annual)	10,773	0.87	0.97	0.34	1.01
		Conditioning Variables			
High Commitment	3,578	0.47	0.50	0.00	1.00
Non-Regulated	10,844	0.49	0.50	1.00	1.00
New Borrower	1,912	0.23	0.42	0.00	1.00
Unconstrained Firm	3,372	0.62	0.49	1.00	1.00
Non-Borrower	59,827	0.60	0.49	1.00	1.00
		Bank Controls			
Assets (log)	10,844	19.16	1.38	18.82	1.55
Loans-to-Assets	10,844	0.49	0.10	.51	0.03
Debt-to-Assets	10,844	0.97	0.37	0.97	0.11
		Firm Controls			
Age (log)	5,880	1.88	0.26	1.95	0.46
Q	5,880	1.76	1.20	1.42	0.84
Profitability	5,880	0.01	0.03	0.01	0.02
Net Leverage	5,880	0.23	0.27	0.24	0.34
Size (log)	5,880	7.73	1.63	7.85	2.45
Net Worth	5,880	0.26	0.27	0.30	0.29

Table 2. Bank Liquidity Requirements and Credit Line Lending: Origination

This table reports output from Eq. (9) . The dependent variables are *Quarterly CL Lending* and *Quarterly CL Origination Count*. The unit of observation is a bank–quarter. *Quarterly CL Lending* is the sum of notional amounts of dollar denominated credit line lending by a given bank in a given quarter, scaled by total bank assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated by a given bank in a given quarter. *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 3* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Bank controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	Quarterly CL Lending				*Quarterly CL Origination Count*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Commitment × *Post Regulation*	-2.367***				-0.206**			
	(0.433)				(0.093)			
High Commitment × *Phase 1*		-0.550				-0.167**		
		(0.336)				(0.082)		
High Commitment × *Phase 2*			-1.282***				-0.220**	
			(0.458)				(0.095)	
High Commitment × *Phase 3*				-1.654***				-0.202*
				(0.531)				(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,377	1,213	1,207	1,183	2,099	1,588	1,603	1,691
R-squared	0.738	0.791	0.801	0.731	0.904	0.905	0.899	0.907

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3. Bank Liquidity Requirements and Credit Line Lending: Facility Pricing

This table reports output from Eq. (10). The dependent variables are *Undrawn Spread* and *Drawn Spread*. The unit of observation is the credit line facility. *Undrawn Spread* is the logarithm of one plus the all-in undrawn spread over the base rate associated with the credit line facility. *Drawn Spread* is the logarithm of one plus the all-in drawn spread over the base rate associated with the credit line facility. *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 3* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Bank controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Facility-level controls include the logarithm of the facility notional amount, the maturity at issue, and the logarithm of one plus the number of syndication agents. Borrower control includes the issuer long term credit rating assigned by Standard and Poor's. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	Undrawn Spread				*Drawn Spread*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Commitment × *Post Regulation*	0.111**				0.071*			
	(0.049)				(0.037)			
High Commitment × *Phase 1*		0.064*				0.039		
		(0.033)				(0.025)		
High Commitment × *Phase 2*			0.069**				0.065**	
			(0.025)				(0.029)	
High Commitment × *Phase 3*				0.139***				0.085**
				(0.036)				(0.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,115	5,346	5,062	5,341	6,115	5,346	5,062	5,341
R-squared	0.556	0.561	0.593	0.564	0.406	0.367	0.396	0.398

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Bank Liquidity Requirements and Credit Line Lending: Origination by Non-regulated Lenders

This table reports output from Eq. (9). The dependent variables are *Quarterly CL Lending* and *Quarterly CL Origination Count*. The unit of observation is a lender–quarter. *Quarterly CL Lending* is the sum of notional amounts of dollar denominated credit line lending by a given lender in a given quarter, scaled by total assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated by a given lender in a given quarter. *Non-Regulated* is an indicator variable that takes the value of 0 for lenders in the Thomson-Reuters' LPC DealScan sample that report FR Y-9C data and 1 for the rest. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q2. Controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio, averaged across all lenders in a given quarter. Lender– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by lender and quarter.

	Quarterly CL Lending				*Quarterly CL Origination Count*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-Regulated × *Post Regulation*	1.048***				0.106**			
	(0.115)				(0.042)			
Non-Regulated × *Phase 1*		0.006				0.097**		
		(0.126)				(0.040)		
Non-Regulated × *Phase 2*			0.596***				0.122***	
			(0.124)				(0.045)	
Non-Regulated × *Phase 3*				1.092***				0.023
				(0.137)				(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,309	2,451	2,452	2,124	5,616	4,699	4,640	4,621
R-squared	0.753	0.847	0.840	0.811	0.903	0.908	0.902	0.914

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5. Bank Liquidity Requirements and Credit Line Lending: Facility Pricing by Non-Regulated Lenders

This table reports output from Eq. (10). The dependent variables are *Undrawn Spread* and *Drawn Spread*. The unit of observation is the credit line facility. *Undrawn Spread* is the logarithm of one plus the all-in undrawn spread over the base rate associated with the credit line facility. *Drawn Spread* is the logarithm of one plus the all-in drawn spread over the base rate associated with the credit line facility. *Non-Regulated* is an indicator variable that takes the value of 0 for lenders in the Thomson-Reuters' LPC DealScan sample that report FR Y-9C data and 1 for the rest. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q2. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q2. *Phase 3* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Lender controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio, averaged across all lenders in a given quarter. Facility-level controls include the logarithm of the facility notional amount, the maturity at issue, and the logarithm of one plus the number of syndication agents. Borrower control includes the issuer long term credit rating assigned by Standard and Poor's. Lender– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by lender and quarter.

	Undrawn Spread				*Drawn Spread*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-Regulated × *Post Regulation*	-0.017*				-0.024***			
	(0.009)				(0.008)			
Non-Regulated × *Phase 1*		-0.005				-0.009*		
		(0.005)				(0.005)		
Non-Regulated × *Phase 2*			0.002				-0.020***	
			(0.011)				(0.007)	
Non-Regulated × *Phase 3*				-0.027**				-0.028***
				(0.009)				(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,369	11,695	11,417	11,859	14,369	11,695	11,417	11,859
R-squared	0.951	0.961	0.958	0.957	0.955	0.961	0.956	0.960

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Bank Liquidity Requirements and Credit Line Lending: Relationship Dynamics

This table reports output from Eq. (9). The dependent variables are *New Borrower CL Lending* and *New Borrower Loan Origination.* The unit of observation is a bank–quarter. *New Borrower CL Lending* is the sum of notional amounts of dollar denominated credit line lending to firms that borrowed from the given bank for the first time in the given quarter, scaled by total bank assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated towards firms that borrowed from the given bank for the first time in the given quarter, scaled by total bank assets. *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 3* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Bank controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	New Borrower CL Lending				*New Borrower Loan Origination*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Commitment × *Post Regulation*	-0.668***				-0.320***			
	(0.125)				(0.068)			
High Commitment × *Phase 1*		-0.374***				-0.182**		
		(0.129)				(0.076)		
High Commitment × *Phase 2*			-0.426**				-0.282***	
			(0.171)				(0.086)	
High Commitment × *Phase 3*				-0.610***				-0.283***
				(0.166)				(0.094)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,055	1,550	1,557	1,583	2,055	1,550	1,557	1,583
R-squared	0.486	0.638	0.614	0.557	0.832	0.858	0.855	0.848

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 7. Bank Liquidity Requirements and Credit Line Lending: Relationship Dynamics of Non-Regulated Lenders

This table reports output from Eq. (9). The dependent variables are *New Borrower CL Lending* and *New Borrower Loan Origination*. The unit of observation is a bank–quarter. *New Borrower CL Lending* is the sum of notional amounts of dollar denominated credit line lending to firms that borrowed from the given bank for the first time in the given quarter, scaled by industry average of total assets. *Quarterly CL Origination Count* is the logarithm of one plus the number of new credit lines originated towards firms that borrowed from the given lender for the first time in the given quarter. *Non-Regulated* is an indicator variable that takes the value of 0 for lenders in the Thomson-Reuters' LPC DealScan sample that report FR Y-9C data and 1 for the rest. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Lender controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio, averaged across all lenders in a given quarter. Lender– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by lender and quarter.

	New Borrower CL Lending				*New Borrower Loan Origination*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-Regulated × *Post Regulation*	0.382***				0.168***			
	(0.030)				(0.048)			
Non-Regulated × *Phase 1*		0.030				0.118***		
		(0.032)				(0.045)		
Non-Regulated × *Phase 2*			0.193***				0.143***	
			(0.034)				(0.050)	
Non-Regulated × *Phase 3*				0.349***				0.089
				(0.042)				(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Lender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,489	3,330	3,304	2,879	6,489	3,330	3,304	2,879
	0.510	0.710	0.682	0.532	0.845	0.868	0.859	0.864

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8. Bank Liquidity Requirements and Credit Line Lending: Lending Strictness

This table reports output from Eq. (10). The dependent variables are *#Covenants*, *Initial Covenant Slack*, $\mathbb{1}$*(Covenants)*, and $\mathbb{1}$*(Secured)*. The unit of observation is a lender–quarter in specifications (1) and (2), and the package deal of which the credit line is a part. *#Covenants* is the logarithm of one plus the average number of covenants (both financial and net worth covenants) included in each package originated by the lender in the quarter. *Initial Covenant Slack* is the distance between the covenant threshold and its level at origination, scaled by the initial level and averaged across all deals originated by the lender in a quarter. $\mathbb{1}$*(Covenants)* is an indicator variable that takes the value 1 for deals that include at least one covenant, and 0 for deals which have no covenants attached. $\mathbb{1}$*(Secured)* is an indicator variable that takes the value of 1 for each credit line deal that is secured by collateral, and 0 otherwise. *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Non-Regulated* is an indicator variable that takes the value of 0 for lenders in the Thomson-Reuters' LPC DealScan sample that report FR Y-9C data and 1 for the rest. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Lender controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio, averaged across all lenders in a given quarter. Lender– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Columns (5) through (8) report pseudo R-squared of *probit* regression. Robust standard errors, reported in parentheses, are dual–clustered by lender and quarter.

	#Covenants		*Initial Covenant Slack*		$\mathbb{1}$*(Covenants)*		$\mathbb{1}$*(Secured)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High-Commitment × *Post Regulation*	0.205**		0.043*		0.482***		0.194**	
	(0.102)		(0.023)		(0.089)		(0.083)	
Non-Regulated × *Post Regulation*		–0.428***		–0.071***		0.136***		0.051***
		(0.068)		(0.016)		(0.034)		(0.022)
Model	*OLS*		*OLS*		*Probit*		*Probit*	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Lender	Yes	Yes	Yes	Yes	No	No	No	No
Quarter	Yes	Yes	Yes	Yes	No	No	No	No
Observations	3,508	7,127	1,452	1,622	12,446	24,232	12,446	24,232
R-squared	0.250	0.207	0.328	0.327	0.196	0.208	0.247	0.253

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 9. Bank Liquidity Requirements and Credit Line Lending: Contract Analyses

This table reports output from Eq. (9). The dependent variables are *Borrower Constraints*, *Early Termination Clause*, *Seniority Clause*, and *Contracting Complexity*. The unit of observation is a bank–quarter. *Borrower Constraints* the logarithm of one plus the number of constraining sentences in a credit line agreement pertaining to the borrower, divided by the total number of constraining sentences in the agreement. *Early Termination Clause* is the maximum of the pairwise cosine similarity between phrases in the document and a pre-determined sample early termination clauses. *Seniority Clause* is the maximum of the pairwise cosine similarity between phrases in the document and a pre-determined sample early termination clauses. *Contracting Complexity* is the mean of the distribution of linguistic entropy (Shannon (1951)) of each word in the document. *High Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of credit line commitments in the preceding quarter and 0 for banks in the lowest tercile of credit line commitments in the preceding quarter. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	Borrower Constraints	*Early Termination Clause*	*Seniority Clause*	*Document Complexity*
	(1)	(2)	(3)	(4)
High-Commitment × *Post Regulation*	0.019**	0.008**	0.004*	0.010**
	(0.008)	(0.003)	(0.002)	(0.005)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Bank	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Observations	952	952	952	952
R-squared	0.186	0.168	0.253	0.242

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10. New Credit Line Borrowers: Aggregate Borrowing and Pricing

This table reports output from Eq. (11). The dependent variables are *Quarterly CL Borrowing*, *Maturity*, *Drawn Spread*, and *Undrawn Spread*. The unit of observation is a firm–quarter. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *Maturity*, is the logarithm of one plus the weighted average maturity of credit lines borrowed by a given firm in a given quarter. *Drawn Spread* is the logarithm of one plus the weighted average all-in drawn spread over the base rate across credit lines borrowed by a given firm in a given quarter. *Undrawn Spread* is the logarithm of one plus the weighted average all-in undrawn spread over the base rate across credit lines borrowed by a given firm in a given quarter. *New Borrower*is an indicator variable that takes the value of 1 for firms borrowing syndicated credit lines for the first time in a given quarter, and 0 for returning borrowers matched on age, size, Q, profitability, net financial leverage, and net worth. Summary statistics of the matched sample are presented in Table C.2. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth. Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter.

	Quarterly CL Borrowing	*Maturity*	*Drawn Spread*	*Undrawn Spread*
	(1)	(2)	(3)	(4)
New Borrower × *Post Regulation*	-0.083*	1.166**	0.190**	0.610**
	(0.047)	(0.549)	(0.094)	(0.233)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Industry × Quarter	Yes	Yes	Yes	Yes
Observations	1,126	1,126	1,126	723
R-squared	0.613	0.201	0.263	0.534

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 11. Credit Line Borrowing and Firm Financing Constraints

This table reports output from Eq. (11). The dependent variables are *Quarterly CL Borrowing* and *Undrawn Spread*. The unit of observation is a firm–quarter. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *Undrawn Spread* is the logarithm of one plus the weighted average all-in undrawn spread over the base rate across credit lines borrowed by a given firm in a given quarter. *Unconstrained Firm*is an indicator variable that takes the value of 1 for firms in the lowest tercile of the size-age index (Hadlock and Pierce (2010)), and 0 for firms in the highest tercile. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 1* is an indicator variable that takes the value of 1 for all four quarters of year 2015 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 2* is an indicator variable that takes the value of 1 for all four quarters of year 2016 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. *Phase 3* is an indicator variable that takes the value of 1 for all four quarters of year 2017 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth. Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter.

	Quarterly CL Borrowing				*Undrawn Spread*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unconstrained Firm × *Post Regulation*	-0.272*				0.218**			
	(0.156)				(0.099)			
Unconstrained Firm × *Phase 1*		-0.333**				0.099		
		(0.169)				(0.070)		
Unconstrained Firm × *Phase 2*			-0.293				0.140**	
			(0.182)				(0.056)	
Unconstrained Firm × *Phase 3*				-0.549***				0.300**
				(0.190)				(0.125)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Industry × Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,440	1,376	1,256	1,201	870	932	794	738
R-squared	0.987	0.995	0.986	0.987	0.925	0.947	0.955	0.938

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 12. Unconstrained Credit Line Borrowers: Firm Heterogeneity

This table reports output from Eq. (11). The dependent variable is *Quarterly CL Borrowing*. The unit of observation is a firm–quarter. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *Unconstrained Firm*is an indicator variable that takes the value of 1 for firms in the lowest tercile of the size-age index (Hadlock and Pierce (2010)), and 0 for firms in the highest tercile. *Debt Due in 1 Year* is the current portion of long term debt, scaled by lagged assets. *Tangibility* is defined following Berger et al. (1996) as *0.715× Receivables + 0.547 × Inventory + 0.535 × Capital*. *Innovation* is the total Q measure, based on firms' innovation capital (Peters and Taylor (2017)). *Default Probability* is the physical probability of default corresponding to Bharath and Shumway (2008), on the last day of the preceding quarter. *Low* and *High* denote lowest and highest terciles of the distribution of a given conditioning variable. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth. Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter.

	Quarterly CL Borrowing							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unconstrained Firm × *Post Regulation*	0.009	-0.131**	-0.173***	0.009	0.102	-0.213**	-0.281***	0.118
	(0.050)	(0.034)	(0.055)	(0.062)	(0.094)	(0.096)	(0.089)	(0.098)
Conditioning Variable	*Debt Due in 1 Year*		*Tangibility*		*Innovation*		*Default Probability*	
Level	Low	High	Low	High	Low	High	Low	High
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Industry × Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	383	366	476	492	426	381	205	294
R-squared	0.826	0.719	0.906	0.959	0.670	0.847	0.787	0.752

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 13. Liquidity Policy Switchers: Financial Policy and Risk

This table reports output from Eq. (11). The dependent variables are *Net Cash*, *Net Leverage*, *Cashflow Volatility*, *Asset Beta*and *Default Probability*. The unit of observation is a firm–quarter. *Net Cash* is cash and short-term investments net of current liabilities, scaled by total assets. *Net Leverage* is the total short- and long-term debt net of cash divided by total assets. *Cashflow Volatility* is constructed following Minton and Schrand (1999) as the coefficient of variation in the quarterly operating cashflow, over the preceeding 24 quarters (six years). *Asset Beta* is calculated by unlevering quarterly stock market beta, estimated using CAPM. *Default Probability* is the physical probability of default corresponding to Bharath and Shumway (2008), on the last day of the preceding quarter. *Non-Borrower* is an indicator variable that takes the value of 1 for a firm that exits the syndicated lending market for credit lines following full implementation of LCR on January 1st, 2017, and did not borrow for three years preceding this date. The variable takes the value 0 for firms that continue to borrow syndicated credit lines following this period. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth. Firm– and Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter.

	Net Cash	*Net Leverage*	*Cashflow Volatility*	*Asset Beta*	*Default Probability*
	(1)	(2)	(3)	(4)	(5)
Non-Borrower × *Post Regulation*	0.082***	0.009***	0.132***	0.063*	0.398**
	(0.019)	(0.003)	(0.022)	(0.026)	(0.157)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Firm	Yes	Yes	Yes	Yes	Yes
Industry × Quarter	Yes	Yes	Yes	Yes	Yes
Observations	36,215	36,204	36,727	26,925	16,286
R-squared	0.675	0.884	0.774	0.155	0.451

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 14. Liquidity Policy Switchers: Firm Outcomes

This table reports output from Eq. (11). The dependent variables are *Profitability*, *New Patents*, *R&D Expenses*, *Investment*, and *Payout Ratio*. *Profitability* is net income divided by lagged total assets. *New Patents* is one plus the logarithm of number of patent applications by the firm in the quarter. *R&D Expenses* is quarterly research and development expenses scaled by total assets. *Investment* is capital expenditures divided by total assets. *Payout Ratio* is the sum of divdends to common and preferred shareholders, plus repurchases, scaled by operating income. The unit of observation is a firm–quarter in columns (1) to (3) and firm –year in columns (4) and (5). *Non-Borrower* is an indicator variable that takes the value of 1 for a firm that exits the syndicated lending market for credit lines following full implementation of LCR on January 1st, 2017, and did not borrow for three years preceding this date. The variable takes the value 0 for firms that continue to borrow syndicated credit lines following this period. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth, excluding those that coincide with the outcome variable. Firm– and Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter in columns (1) to (3), and industry and year in columns (4) to (6).

	Profitability	*New Patents*	*R&D Expenses*	*Investment*	*Payout Ratio*
	(1)	(2)	(3)	(4)	(5)
Non-Borrower × *Post Regulation*	0.002**	0.368**	0.026***	0.003**	0.717***
	(0.001)	(0.147)	(0.007)	(0.001)	(0.098)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects					
Firm	Yes	Yes	Yes	Yes	Yes
Industry × Quarter	Yes	Yes	Yes	No	No
Industry × Year	No	No	No	Yes	Yes
Observations	33,866	33,866	17,423	5,596	5,596
R-squared	0.608	0.878	0.927	0.858	0.300

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix A Composition of HQLA

Table A.1. Select list of HQLA eligibility

This table reports a select of assets that qualify as High Quality Liquid Assets (HQLA) for covered banks to meet LCR obligations. Level 1 assets are those that incur no discounts to fair value and no restrictions on their total composition to meet HQLA holding requirements. Level 2 assets may account for upto 40% of total HQLA, and are further classified into Level 2A and 2B. Level 2A assets attract 15% discount to fair value across the board. Level 2B assets cannot constitute more than 15% of total HQLA and attract 50% discount to fair value.

Level 1 Assets *(Upto 100% of HQLA)*	**Level 2 Assets** *(Upto 40% of HQLA)*
Haircut = 0%	**Level 2A Assets**
	Haircut = 15%
■ Excess reserves held at a Federal Reserve Bank ■ Withdrawable reserves held at a foreign central bank ■ Securities issued or guaranteed by the U.S. Treasury ■ Securities issued or guaranteed by a U.S. government agency whose obligations are explicitly guaranteed by the U.S. government ■ OECD sovereign debt without default or was restructuring in previous 5 years.	■ Claims on or guaranteed by a U.S. government-sponsored enterprise (e.g., Fannie Mae, Freddie Mac). ■ Claims on or guaranteed by a sovereign entity or a multilateral development bank assigned a 20% risk weight under U.S. Basel III.
	Level 2B Assets *(Upto 15% of HQLA)*
	Haircut = 50%
	■ Corporate debt securities issued by non-financial companies (rated AA– or higher) ■ Publicly traded common equities issued by non-financial companies that are included in the Russell 1000 Index.

Appendix B Bank Size and LCR Exposure

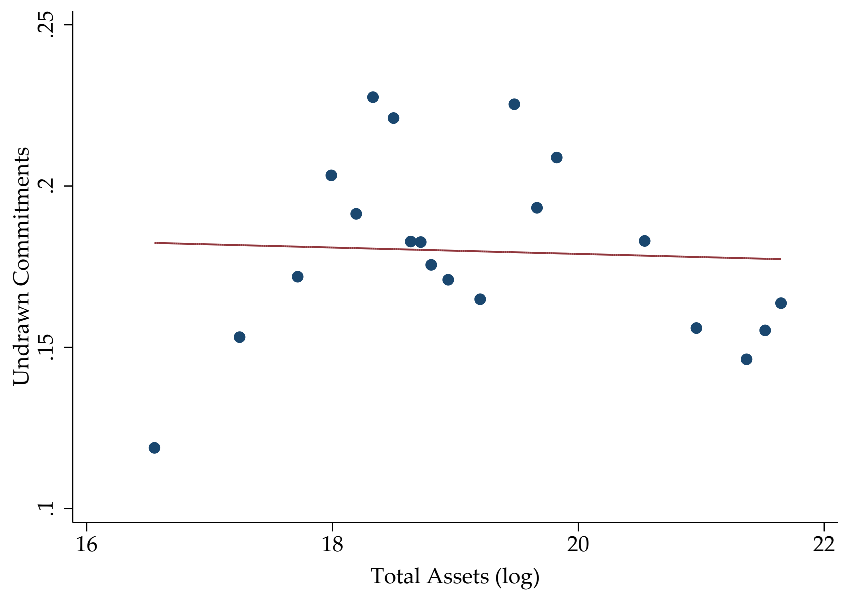


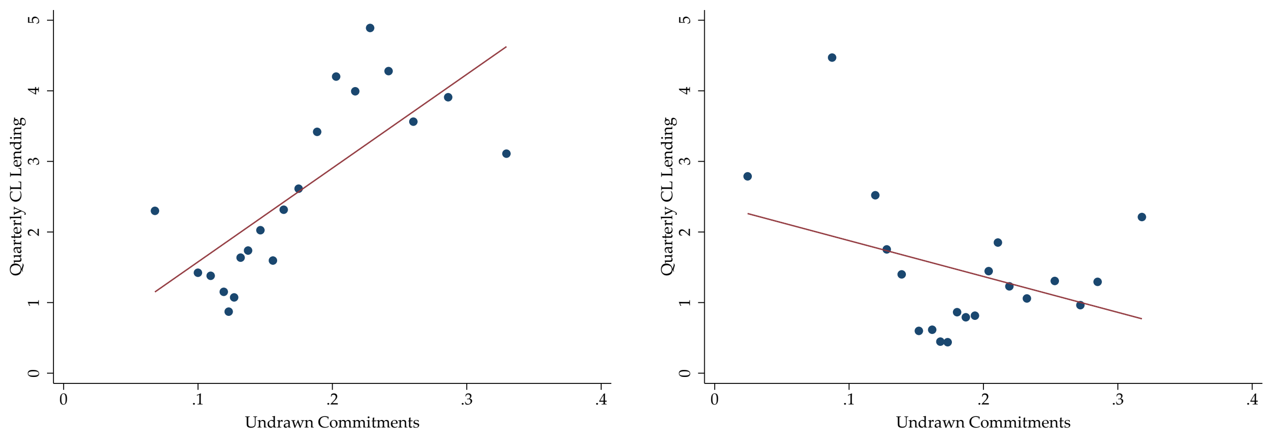
Figure B.1. Size and Undrawn Credit Lines. This figure plots the cross-sectional relationship between size (logarithm of total assets) and total undrawn credit line commitments for the pre-LCR period (for banks in the DealScan sample). Data are represented in the form of 20 equal-sized bins based on the cross-sectional distribution of the depicted variables.

Table B.1. Select List of BHCs by LCR Exposure

This table reports the list of 15 largest Banks Holding Companies (BHC), based on total assets and a list of the 15 BHCs with the ratios highest undrawn commitments to assets (*Undrawn Commitments*), averaged over the pre-LCR period of 2013:Q1 to 2014:Q3. Bank names are as of December 2020 accounting for mergers and acquisitions, obtained from the National Informatics Center (NIC) and are matched based on the FR Y-9C identifier.

Bank Holding Company	*Undrawn Commitments* Rank	Asset Rank
BHCs by *Undrawn Commitments*		
MUFG Americas Holdings Corp.	1	24
Citizens Financial Group, Inc.	2	23
J.P. Morgan Chase & Co.	3	1
HSBC North America Holdings Inc.	4	13
Keycorp	5	31
BBVA USA Bancshares, Inc.	6	40
Morgan Stanley	7	6
U.S. Bancorp	8	7
Citigroup Inc.	9	4
Northern Trust Corporation	10	35
The PNC Financial Services Group, Inc.	11	8
CIBC Bancorp USA, Inc. (formerly PrivateBancorp)	12	80
TD Group US Holdings llc	13	10
Bank of America Corporation	14	2
Truist Financial Corporation (formerly BB&T)	15	16
BHCs by Assets		
J.P. Morgan Chase & Co.	3	1
Bank of America Corporation	15	2
Wells Fargo & Company	17	3
Citigroup Inc.	9	4
The Goldman Sachs Group	24	5
Morgan Stanley	7	6
U.S. Bancorp	8	7
The BNY Mellon Corproation	29	8
The PNC Financial Services Group, Inc.	12	9
Capital One Financial Corporation	48	10
HSBC North America Holdings Inc.	4	11
TD Group US Holdings llc	14	12
State Street Corporation	30	13
Truist Financial Corporation (formerly BB&T)	16	14
Suntrust Banks, Inc.	19	15

Appendix C Additional Figures and Tables



(A) Pre-LCR

(B) Post-LCR

Figure C.1. Credit Line Commitments and Origination. This figure plots the cross-sectional relationship between banks' pre-existing undrawn commitments and new credit line origination (*Quarterly CL Lending*). Panel A presents the relationship for the pre-LCR period (2013:Q1 to 2014:Q3). Panel B presents the relationship for the post-LCR period (2017:Q1 to 2018:Q2). Data are represented in the form of 20 equal-sized bins based on the cross-sectional distribution of the depicted variables.

Table C.1. Robustness to Alternative Cutoffs of Credit Line Commitments

This table reports output from Eq. (9) . The dependent variables are *Quarterly CL Lending* and *Quarterly CL Origination Count*. The unit of observation is a bank–quarter. *Quarterly Lending* is the sum of notional amounts of dollar denominated credit line lending, scaled by total bank assets. *Quarterly Loan Origination* is the logarithm of one plus the number of new credit lines originated in the quarter. *High Commitment (Median)* is an indicator variable that takes the value of 1 for banks above the median of credit line commitments in the preceding quarter and 0 for banks below the median of credit line commitments in the preceding quarter. *High Commitment (Quartiles)* is an indicator variable that takes the value of 1 for banks in the highest quartile of credit line commitments in the preceding quarter and 0 for banks in the lowest quartile of credit line commitments in the preceding quarter. *High Commitment (Quintile)* is an indicator variable that takes the value of 1 for banks in the highest quintile of credit line commitments in the preceding quarter and 0 for banks in the lowest quintile of credit line commitments in the preceding quarter. *Undrawn Commitments* is the ratio of one-quarter lagged credit line commitments to total assets. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Bank controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	Quarterly CL Lending				*Quarterly CL Origination Count*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Commitment (Median) × *Post Regulation*	-1.111***				-0.175***			
	(0.359)				(0.068)			
High Commitment (Quartiles) × *Post Regulation*		-1.846***				-0.307***		
		(0.462)				(0.112)		
High Commitment (Quintiles) × *Post Regulation*			-1.876***				-0.419***	
			(0.540)				(0.135)	
Undrawn Commitments × *Post Regulation*				-13.629***				-1.889***
				(2.700)				(0.501)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,075	1,039	832	2,075	3,151	1,578	1,253	3,151
R-squared	0.790	0.843	0.835	0.791	0.862	0.908	0.907	0.863

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C.2. Summary Statistics of Matched Sample (*New Borrower*)

This table reports the summary statistics of the matched sample corresponding to results presented in Table 10. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *New Borrower* is an indicator variable that takes the value of 1 for firms borrowing syndicated credit lines for the first time in a given quarter, and 0 for returning borrowers. The matching variables are age (years since IPO), size (logarithm of assets), *Q* (market-to-book value of equity), profitability (net income divided by lagged assets), net financial leverage, and net worth (non-cash total assets minus total liabilities, divided by non-cash assets).

Variable	N	Mean	Median	SD	IQR
New Borrower = 1					
Quarterly CL Borrowing	435	0.24	0.16	0.26	0.24
Age (log)	435	1.84	1.79	0.24	0.47
Q	435	1.92	1.45	1.60	1.00
Profitability	435	0.00	0.01	0.05	0.02
Net Leverage	435	0.13	0.13	0.29	0.38
Size (log)	435	7.44	7.52	1.75	2.55
Net Worth	435	0.26	0.30	0.29	0.33
New Borrower = 0					
Quarterly CL Borrowing	1,479	0.24	0.15	0.28	0.24
Age (log)	1,479	1.84	1.79	0.25	0.47
Q	1,479	1.84	1.44	1.35	0.95
Profitability	1,479	0.00	0.01	0.04	0.02
Net Leverage	1,479	0.14	0.15	0.28	0.36
Size (log)	1,479	7.50	7.58	1.69	2.45
Net Worth	1,479	0.27	0.30	0.27	0.31

Table C.3. Robustness to Alternate Measures of Firm Constraint

This table reports output from Eq. (11). The dependent variable is *Quarterly CL Borrowing*. The unit of observation is a firm–quarter. *Quarterly CL Borrowing* is the total notional amount of credit line borrowing by a given firm in a given quarter. *Unconstrained Firm (*Size) is an indicator variable that takes the value of 1 for firms in the highest tercile of the distribution of assets, and 0 for firms in the lowest tercile. *Unconstrained Firm (*Rated) is an indicator variable that takes the value of 1 for firms that are assigned an issuer credit rating by S&P, and 0 for firms in that are not assigned an issuer credit rating. *Unconstrained Firm (*Investment Grade) is an indicator variable that takes the value of 1 for firms with an S&P credit rating of BBB– or higher, and 0 for firms with a credit rating of BB+ or lower. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Firm controls are one quarter lagged age, size, Q, profitability, net financial leverage, and net worth. Industry × Quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by industry and quarter.

	Quarterly CL Borrowing		
	(1)	(2)	(3)
Unconstrained Firm (Size) × *Post Regulation*	–0.176**		
	(0.062)		
Unconstrained Firm (Rated) × *Post Regulation*		–0.258***	
		(0.108)	
Unconstrained Firm (Investment Grade) × *Post Regulation*			–0.351***
			(0.132)
Controls	Yes	Yes	Yes
Fixed Effects			
Industry × Quarter	Yes	Yes	Yes
Observations	1,791	2,645	998
R-squared	0.929	0.895	0.449

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix D Bank Capital Requirements and Credit Lines

In order to attribute the observed credit line lending outcomes to the liquidity-oriented rules of Basel III, it is important to eliminate the possibility that these outcomes are driven by the capital requirements demanded therein. A key difference lies in how these rules differentially impact credit lines and term loans. Capital requirements apply uniformly to both of these classes of lending, whereas the LCR impacts only credit lines — the reason being that in the case of term loans, all of the expected outflow occurs right when the loans are written. In the case of credit lines, the corresponding risk-weighted assets are calculated by applying a credit conversion factor (CCF) to the undrawn portion, and the typical risk weights corresponding to the borrower are applied to this converted amount. The CCF ranges between 0% and 50% for most credit lines, depending on the term of the credit line and its *callability*, which translates to lower capital requirements to the lender compared to an equivalent term loan. In fact, in the extreme case, a capital-constrained lender driven by the objective of reducing the capital requirement burden would be better off substituting term lending with credit line lending. In a more realistic scenario, capital constraints uniformly affect both the term lending and credit line lending of the bank, with credit lines being one component of the banks' overall lending. This, in turn, would imply that banks with the highest levels of overall lending are the most constrained in terms of credit line lending and the observed reduction is a natural spillover of such banks contracting their overall lending portfolio.

To formally investigate this notion, I modify the base specification in Eq. (9) by conditioning on terciles of banks' total outstanding loans and alternatively on their total loans plus undrawn commitments. Were this alternative explanation to hold, such a conditioning should yield analogous results to the baseline results, that is, higher capital-constrained banks reduce credit line lending more. The results of this analysis are reported in Table D.1. The results show that such a conditioning does not yield statistically significant coefficient estimates for either the lending notional or the number of credit line originations. In fact, even the economic magnitude of the difference-in-differences coefficient on the lending notional is close to zero, indicating that there is no discernible difference in the credit line lending activity of capital constrained banks *vs.* the rest. I interpret this as suggestive evidence that the observed outcomes are driven by liquidity requirements rather than capital requirements.

Table D.1. Bank Loan Exposure and Credit Line Lending

This table reports output from Eq. (9) . The dependent variable is *Quarterly CL Lending*. The unit of observation is a bank–quarter. *Quarterly CL Lending* is the sum of notional amounts of dollar denominated credit line lending, scaled by total bank assets. *High Loans & Commitment* is an indicator variable that takes the value of 1 for banks in the highest tercile of loans plus credit line commitments, scaled by assets, in the preceding quarter and 0 for banks in the lowest tercile of loans plus credit line commitments in the preceding quarter. *High Loans* is an indicator variable that takes the value of 1 for banks in the highest tercile of loans in the preceding quarter and 0 for banks in the lowest tercile of loans in the preceding quarter. *Post Regulation* is an indicator variable that takes the value of 1 for each quarter including and after 2017:Q1 and 0 for each quarter beginning 2013:Q1 until 2014:Q3. Controls are one quarter lagged logarithm of total assets, loan–to–asset ratio, and debt–to–equity ratio. Bank– and quarter–fixed effects are included as indicated. All regressions are estimated over the 2012:Q1 to 2018:Q2 period. Robust standard errors, reported in parentheses, are dual–clustered by bank and quarter.

	Quarterly CL Lending		*Quarterly CL Origination*	
	(1)	(2)	(3)	(4)
High Loans & Commitment × *Post Regulation*	0.000		–0.118	
	(0.001)		(0.193)	
High Loans × *Post Regulation*		0.001		0.189
		(0.001)		(0.161)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Bank	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Observations	1,377	1,377	1,377	1,377
R-squared	0.571	0.478	0.865	0.776

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix E Distance from Financial Centers

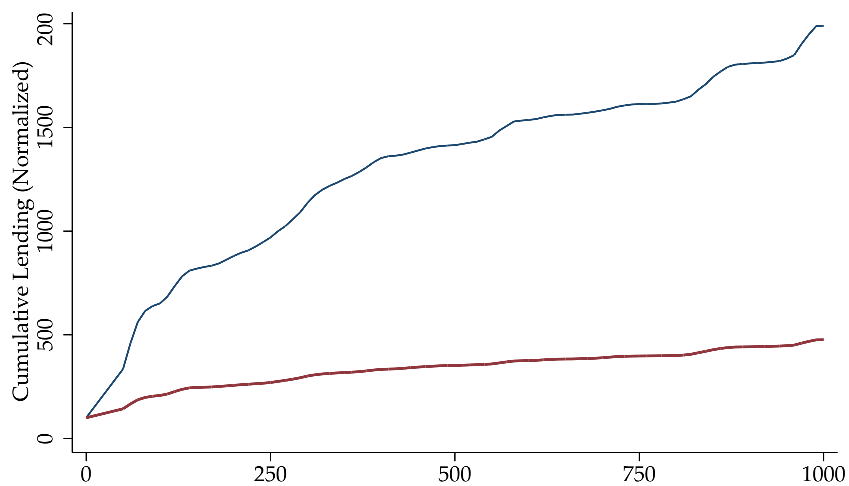


Figure E.1. Geographical Dispersion of Lending. This figure plots the cumulative quarterly credit line lending as a function of the borrowing firm–headquarters' distance from the nearest major economic center. The plots correspond to regulated banks (in blue) and non-regulated banks (in red). Major economic centers are defined as the 10 largest metropolitan statistical areas by GDP, based on data from Bureau of Economic Analysis as of 2013:Q1; plus Washington D.C. The series are indexed to 100 for within–MSA lending.