# U.S. monetary policy and credit risk of new corporate credit lines

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Abstract: For U.S. corporations, banks originate credit lines in larger volumes than those of term loans. Yet there is not much known about the existence and nature of a risk-taking channel of monetary policy that operates through the former. In contrast to the evidence for term loans, such a channel for credit lines, on the surface, does not exist. But taking into account optionalities built into credit lines changes this naive conclusion. Banks do originate larger credit lines to the riskiest borrowers in response to lower U.S. policy rates when they structure the pricing of these lines to discourage their usage. That is, banks bet on these lines to largely remain off their balance sheets as unfunded commitments. Such a risk-taking response is more pronounced for contracts that include cash-flow covenants and for banks that face weaker supervision or market discipline. The response is less pronounced for banks with stronger capital positions. After a period of low interest rates, some banks that originate ax ante riskier but unlikely-to-be-drawn credit lines may be less prepared for en masse drawdowns in a systemic stress episode, such as a pandemic-triggered crisis.

Keywords: Corporate credit lines; optionalities of credit lines; liquidity shocks for banks; risk-taking channel of monetary policy; supervision and market discipline of banks.

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# 1 Introduction

For U.S. corporations, originations by banks of credit lines far exceed those of term loans, yet there is not much known about the existence and nature of a risk-taking channel of monetary policy that operates through the latter. In contrast to a term loan, a credit line gives borrowers options to draw down, repay, and reborrow over a term. Corporations typically use credit lines to cushion their access to the commercial paper market, to support their working capital, or even to fund a merger & acquisition. While borrowers of credit lines are, on average, safer than those of term loans, there is still a large mass of risky borrowers that seek substantial credit lines. Moreover, given that borrowers are more likely to draw on credit lines when they are in trouble, even ex ante safe credit line commitments may become ex post risky drawn credit lines on banks' balance sheets. And while the banks may cope with idiosyncratic drawdowns by risky borrowers, systemic drawndowns, such as those in a pandemic, may strain the banks and cause financial stability issues and cutbacks in the supply of credit to the broader economy.

In this paper, we study a novel risk-taking channel of U.S. monetary policy that operates through originations of syndicated credit lines by U.S. and non-U.S. banks to larger U.S. corporations. We pay particular attention to the contract features of credit lines, in particular those that dissuade borrowers from drawing down their lines and encourage them to safeguard cash flow. What we have in mind is the following. Banks make material profits from originations and maintenance of credit lines before they are drawn. Lower interest rates may encourage banks to originate larger volumes of credit lines, in particular to riskier borrowers, in search for returns. However, banks recognize that line drawdowns are, first of all, a liquidity shock because they have to fund them. They also recognize that line drawdowns are a capital shock because drawn lines appear on their balance sheets, boosting total and risk-weighted assets. Therefore, banks may protect themselves against such liquidity and capital shocks by reducing the likelihood of line drawdowns through the contract features.

We show that, in contrast to the evidence for term loans, a risk-taking channel of U.S. monetary policy, on the surface, does not operate in the market for syndicated credit lines: Banks appear to originate smaller credit lines to the riskiest borrowers in response to lower interest rates. However, taking into account the contract features of riskier credit lines changes this naive conclusion. We find that banks do originate larger credit lines to risky, SG-rated borrowers in response to lower U.S. policy rates when they expect these lines to remain undrawn. That is, our findings are consistent with banks betting on these lines to remain off their balance sheets as unfunded commitments. Such a risk-taking response is more pronounced for contracts that include cash-flow safeguards and for banks that face weaker supervision and market discipline. The response may be less pronounced for banks with stronger capital positions. The response of banks with stronger liquidity positions is uncertain, a finding that possibly reflects a relatively limited sample size and certainly warrants further examination. To illustrate the economic significance, we show that, under a contract with cash-flow covenants, a bank may increase the amount of a unlikely-to-drawn credit line to a risky, SG-rated borrower by nearly 20 percent in response to a one-standard-deviation decline in the U.S. policy rate. For safe, IG-rated borrowers, the risk-taking channel operates in "reverse": Banks increase amounts of credit lines in response to higher policy rates.

We suggest that, after a prolonged period of low interest rates, some banks that originate ex ante riskier but less-likely-to-be-drawn lines of credit could be less prepared to handle en masse drawdowns in a systemic stress episode, such as a pandemic-triggered crisis. Stress in these banks may have financial stability implications, and it may lead to a cutback in the supply of credit to the economy.

We contribute to a few literature strands: 1) Risk-taking channels of monetary policy; 2) bank management of liquidity and capital risks; and 3) optionalities of credit lines and their pricing. The first strand mostly focuses on domestic or global risk-taking channels of monetary policy that operate through banks that originate bilateral or syndicated term loan—for example, Jimenez, Ongena, Peydro, and Saurina (2014), Ioannidou, Ongena, and Peydro (2015), Dell'Ariccia, Laeven, and Suarez (2017), Altavilla, Boucinha, Peydro, and Smets (2019), and others. This literature, however, does not say much about a risk-taking channel of monetary policy that operates through credit lines. It also mostly looks at credit risk of loans being originated rather than amounts of risky loans being originated. The other two strands do not incorporate monetary policy into analysis, albeit may well deal with cyclical issues. Among the papers in these two strands, we draw mostly from Berg, Saunders, and Steffen (2016) that examine optionalities of credit lines and the ways banks manage and price them. For these two strands, we shed light on how banks deal through contract terms with liquidity and credit risks in credit line originations. Overall, we shed light on how banks approach originating and pricing risky credit lines in response to changes in policy rates thorough multiple U.S. monetary policy cycles, which include the dot com boom and bust, the 2007-09 financial crisis, and the period of unconventional monetary policy.

For our analysis, we merge well-known data sets: Refinitiv Loan Pricing Corporation DealScan for information on syndicated loans; Moody's Analytics CreditEdge for expected default frequencies (EDFs) of syndicated loan borrowers; Barth, Caprio, and Levine (2013)' surveys of micro- and macroprudential powers and market discipline measures that banks face in their headquarter countries; and, finally, Capital IQ for characteristics of U.S. and foreign banks. We focus on a cut of the merged data that covers originations of U.S. dollar-denominated credit lines for U.S. borrowers by U.S. and foreign banks for a couple of reasons. First, U.S. borrowers represent the overwhelming majority of borrowers of U.S. dollar credit lines and the literature has a good understanding of the specifics of their contract terms. Second, the literature also has a good understanding of drawdown behavior of U.S. borrowers, including that in a prolonged stress episode such as the 2007-09 financial crisis.

We adapt the empirical approaches in papers on a quantity-based risk-taking channel of monetary policy that operates through term loans and other banking papers to work for credit lines. The latter include Altavilla, Boucinha, Peydro, and Smets (2019) that focuses on amounts of risky bilateral term loans—rather than credit risk of loans—that banks originate in response to euro-area policy rates. In turn, Lee, Liu, and Stebunovs (2020) look at amounts of risky syndicated term loans that lenders originate in response to U.S. policy rates. It exploits the syndication features for identification: Within a syndicate, multiple lenders of different characteristics lend different amounts to the same borrower on exactly the same terms. This setup builds on Khwaja and Mian

(2008) where banks of different characteristics lend to the same borrowers but not on the same terms. In turn, we modify Lee, Liu, and Stebunovs (2020)'s approach to capture the option features of credit lines. Specifically, in light of Berg, Saunders, and Steffen (2016) and other papers, we differentiate credit lines by their likelihood of being drawn. We identify the effects of monetary through interaction terms of policy rates and bank or contract terms, as in Kashyap and Stein (2000). The causal inference is further strengthened through a battery of (time) fixed effects.

The reminder of the paper is organized as follows. Section 2 places the paper in the literature. Section 3 describes the key features of syndicated credit lines and a measure of ex ante credit risk of borrowers of syndicated term loans and credit lines. Section 4 covers the empirical methodology and section 5 discusses the estimation results. Section 6 presents some robustness checks and section 7 concludes with a few remarks on the implications of our findings for financial stability issues and the supply of credit to the broader economy.

# 2 Literature

We contribute to a few literature strands: 1) Risk-taking channels of monetary policy; 2) bank management of liquidity and capital risks; and 3) optionalities of credit lines and their pricing.

The first strand mostly focuses on domestic or global risk-taking channels of monetary policy that operate through banks that originate bilateral or syndicated term loan. See, for example, Jimenez, Ongena, Peydro, and Saurina (2014), Ioannidou, Ongena, and Peydro (2015), Dell'Ariccia, Laeven, and Suarez (2017), Lee, Liu, and Stebunovs (2019), and others. The strand also documents that banks accommodate risk choices of non-banks in originations and subsequent sales of syndicated term loans in the secondary market, see Aramonte, Lee, and Stebunovs (2019). The papers document a causal relationship between lower short- and longer-term interest rates and originations or investments into riskier term loans or structured products backed by term loans. Search-for-yield is the key for such behavior, which is more pronounced for lenders with stronger capacity to absorb potential losses. This literature, however, does not say much about a risk-taking channel of monetary policy that operates through credit lines.

The other strands do not incorporate monetary policy into analysis, albeit may well deal with cyclical issues. In these strands, some papers argue that banks have a unique ability to hedge against market-wide liquidity shocks and, thus, provide credit lines and support the market for commercial paper. For example, Gatev and Strahan (2006) argue that deposit inflows into banks provide funding for loan demand shocks that follow declines in market liquidity. They conclude that banks can insure firms against systematic declines in liquidity at lower cost than other financial institutions. These flows allow banks to meet loan demand from borrowers drawing funds from commercial paper backup lines without running down their holdings of liquid assets. They also provide evidence that implicit government support for banks during crises explains these funding flows.

However, more recent research tempers this take on banks' ability to insure systemic liquidity shocks. Berrospide, Meisenzahl, and Sullivan (2012) document that drawdowns of credit lines had already increased in 2007, ahead of the great recession. The surge in drawdowns occurred precisely when disruptions in bank funding markets began. Some papers argue that banks are not set up to absorb systemic risk from en masse drawdowns of credit lines. For example, Acharya, Almeida, and Campello (2013) suggest that banks can create liquidity for firms by pooling their idiosyncratic risks. As a result, bank credit lines for firms with greater exposures to aggregate risk may be costlier and, thus, such firms may opt to hold more cash in spite of the incurred liquidity premium. Indeed, they find that firms with higher betas have a higher ratio of cash to credit lines and face greater costs on their lines. In times of heightened aggregate volatility, banks exposed to undrawn credit lines become riskier; bank credit lines feature fewer initiations, higher spreads, and shorter maturity; and, firms cash reserves rise. In turn, Acharya and Mora (2015) question banks advantage as liquidity providers in a financial crisis. They find that while banks honored credit lines drawn by firms during the 2007-09 financial crisis, this liquidity provision was only possible because of explicit, large support from the government and governmentsponsored agencies—echoing Gatev and Strahan (2006). At the onset of the crisis, aggregate deposit inflows into banks weakened and their loan-to-deposit shortfalls widened. These patterns were pronounced at banks with greater undrawn commitments. Such banks sought to attract deposits by offering higher rates, but the resulting private funding was insufficient to cover shortfalls and they reduced new credit.

Berg, Saunders, and Steffen (2016) provide evidence that the main purposes of fees in line contracts is to deal optionalities that credit lines provide to borrowers. Consitently with existing theories, they find that: (1) fees are used to price options embedded in contracts such as the drawdown option for credit lines, and (2) fees are used to screen borrowers based on the likelihood of exercising these options. They find that upfront fees and spreads on undrawn lines are larger for high-volatility borrowers, as measured by volatility of either equity or profitability. Furthermore, credit lines with a spread-increasing performance-pricing schedule have lower upfront fees and a lower all-in-undrawn spreads, consistent with the view that the drawdown option contained in credit lines is worth less to the borrower if the loan spread increases as borrowers creditworthiness deteriorates. They also find evidence consistent with borrowers self-selecting into contracts based on their private information about the likelihood of exercising the drawdown option. They find that borrowers that pay a lower all-in-undrawn spread and a higher all-in-spread-drawn are less likely to draw on their line of credit. For example, borrowers in the lowest ratio of the two spreads quintile have a higher average usage rate in the first three years after loan origination than that of borrowers in the highest ratio of the spreads quintile. Furthermore, average usage rates are almost 10 percentage points lower for borrowers whose contracts specify a utilization feewhich applies when a borrowers usage exceeds a pre-specified commitment threshold.

The literature has a good understanding of the patterns of credit line drawdowns, which, not surprisingly, mostly reflect borrower troubles. Berg, Saunders, and Steffen (2016) show that firms are more likely to draw on their lines of credit when their economic situation deteriorates—based on realized equity returns over a few years following loan origination, with borrowers with the lowest returns posting significantly higher drawdowns. Chang, Chen, Dasgupta, and Masulis (2019) find that unrated and, to a lesser extent, intermediate-rated firms draw down credit lines most frequently when capital market conditions are unfavorable and that tighter covenants are one major reason firms repay credit lines as market conditions improve. Berrospide, Meisenzahl, and Sullivan (2012) find that while smaller and lower-rated firms use their credit lines more intensively in general, larger and higher-rated firms were more likely to draw on their credit lines during the 2007-09 crisis.

Drawdowns of credit lines may be a drag on banks' capital for a prolonged period. Chang, Chen, Dasgupta, and Masulis (2019) find that credit line drawdowns are an important source of long-term finance for capital expenditures and acquisitions for all but the highest rated firms. They find that two-thirds of drawdowns are repaid within 2 years, while other sources of long-term debt financing are substituted. In this way, long term credit lines act like a bridge financing mechanism. Moreover, even in a crisis, banks appear not to shed their exposures to credit lines. For example, for the U.S. evidence for the 2007-09 crisis, Berrospide, Meisenzahl, and Sullivan (2012) find that covenant-induced reduction of credit supply to be small, and they find almost no evidence of credit line cancellations. Thus, banks may be stuck with substantial exposures to higher risk borrowers for a couple of years, even in a crisis, which may put material pressure on their capital positions.

For these two former strands, we shed light on how banks deal through contract terms with liquidity and credit risks in credit line originations. Overall, we shed light on how banks approach originating and pricing risky credit lines in response to changes in policy rates thorough multiple U.S. monetary policy cycles, which include the dot com boom and bust, the 2007-09 financial crisis, and the period of unconventional monetary policy.

# 3 Term loans and credit lines

In this section, we provide a run-through of the main differences between syndicated term loans and credit lines. Term loans and credit lines are profoundly distinct types of credit. While term loans are loans of fixed amounts and maturities that are disbursed at origination, credit lines—or revolving lines of credit—are commitments that allow borrowers to repeatedly draw and repay funds up to a limit until maturity. Subsequently, term loans and credit lines have contract terms that may not be comparable. Because of the complementarity of term loans and credit lines, credit agreements between lenders and borrowers often have loans paired with credit lines. However, many of the agreements consist solely of credit lines. revolving lines of credit.[1]

In our data-driven illustrations, we focus on U.S. dollar-denominated loans and lines that U.S. and foreign banks originated for U.S. borrowers over 1995-2019. Foreign banks account for about 45 percent originations by volume, with the percentage climbing higher in the past decade.

Before we discuss credit risk of term loans and credit lines, we explain our choice for the measure of ex ante credit risk of borrowers. Because the syndicated loan data do not provide ex ante credit risk measures and we have limited options for such a measure.[2] Following Lee, Liu, and Stebunovs (2019), we rely on Moody's Analytics CreditEdge EDFs—annualized, point-in-time probabilities

[1] This pattern documented byRoberts and Sufi (2009) still holds in the more recent data.

[2] As an alternative to the vendor-supplied DealScan, we considered the federal bank supervisors' Shared National Credit program that collects the data on syndicated term loans and credit lines that meet certain criteria, see Aramonte, Lee, and Stebunovs (2019) for details. But we opted against using the program for a couple of reasons. First, it collects a more limited set of contract terms than DealScan. Second, and more importantly, it has begun collecting probabilities of default (PDs) only beginning late 2009, making it impossible to capture multiple monetary policy cycles and set a pre-crisis baseline.

of default at various horizons—objective, data-driven measures of ex ante borrower credit risk that are available for a larger number of financial and non-financial firms than the number of firms with credit ratings. These EDFs are based on the structural debt pricing model of Merton (1974) and historical global corporate default data and are widely used in pricing credit. We use the most recent vintage of the EDF data that incorporates information from the financial crisis and the post-crisis period.[3] We then merge the EDF data and the Refinitiv LPC DealScan data by borrowers' names and other details using the matching algorithm in Cohen, Friedrichs, Gupta, Hayes, Lee, Marsh, Mislang, Shaton, and Sicilian (2018). For a given loan-borrower EDF match, we retain an EDF for a horizon that approximates the maturity of the loan or line. The term structure of EDFs is predominantly upward sloping (credit risk is higher at longer horizons). Because of lengthy maturity of contracts, assessments of long-term credit risk appear to be particularly important, perhaps especially so for credit lines, which may remain undrawn until distant future.

Having the credit risk assessment of a given loan-borrower match be same across the banks—free of bank-specific judgment—has an important advantage. As Plosser and Santos (2018b) find, banks with less capital report to regulators lower risk estimates for the same syndicate loans than banks with more capital, consistent with an effort to mitigate capital requirements. Worryingly, the downward bias is greater for large, risky, and opaque credits.

Term loans are materially riskier than credit lines, see figure 1 for a box plot representation of the respective distributions. The distributions of EDFs have similar left tails. But the median EDF and the 75th quartlie of the borrowers of term loans are materially higher. Then, both distributions of EDFs have similarly long right tails. Table 1, which maps EDFs into more familiar senior debt ratings, helps to emphasize further the differences in the distributions.[4] The (relative) mass of IG-rated borrowers of credit lines is larger that than of term loans. The IG-rated borrowers of credit lines are marginally less risky than the IG-rated borrowers of term loans. The mass of SG-rated borrowers of credit lines is smaller than that of term loans, but their default risk is similar. While the masses of non-rated borrowers are similar, the default risk of non-rated borrowers of credit lines is about half of that of non-rated credit line borrowers. Separately, we note that the 90th percentile of EDFs of IG-rated borrowers of credit lines is about 90 basis points, a bit higher than the median of EDFs for SG-rated borrowers, figure 2. Thus, we consider the 1 percent threshold for EDFs as a cut-off that separates safe and risky borrowers.[5]

The maturities of term loans and credit lines are comparable, see figure 3. Both typically range between 0 and 8 years, the median maturity of term loans at 5 years is one year longer than that of credit lines. We note that credit lines with the maturity of one year or shorter account for 15 percent of the credit lines, with the bulk of them recorded pre-2005, before the implementation of

[3]See Nazeran and Dwyer (2015) for a detailed description of the modeling methodology.

[4]Senior debt ratings are based on the scale from Moody's. The junk SG debt rating is for obligations that rated C: The lowest-rated class of bonds and are typically in default, with little prospect for recovery of principal and interest.

[5]As a check of our the threshold, we refer to Aramonte, Lee, and Stebunovs (2019) that use the Shared National Credit data to map one-year, through-the-cycle PDs of term loans into ratings of borrowers. They document that the median PD for loans to IG-rated borrowers is 0.26 percent and the 90th percentile is 1 percent. They also document that a large share of term loans made to SG-rated borrowers have PDs comparable with PDs of term loans made to IG-rated borrowers.

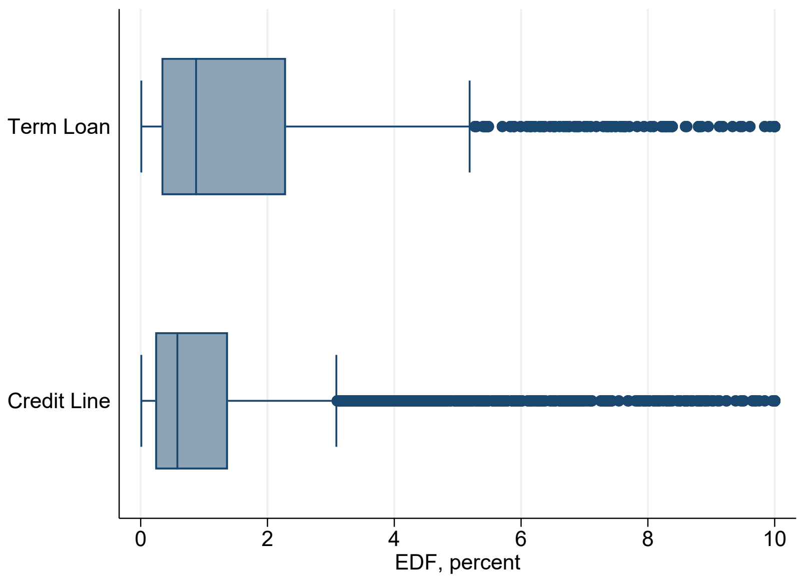


Figure 1: Distributions of loan and line EDFs

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tails are abridged at 10 percent.

Table 1: Distributions of ratings

| Senior debt rating | Term loans EDF, pct 50th pctl | Term loans EDF, pct average | Term loans freq., pct | Credit lines EDF, pct 50th pctl | Credit lines EDF, pct average | Credit lines freq., pct |
|---|---|---|---|---|---|---|
| IG | 0.21 | 0.53 | 17.73 | 0.21 | 0.39 | 22.31 |
| SG | 0.75 | 1.67 | 19.55 | 0.85 | 1.67 | 12.83 |
| junk SG | 3.40 | 8.26 | 1.04 | 3.53 | 10.16 | 0.97 |
| Non-rated, unavailable | 1.20 | 3.17 | 61.68 | 0.69 | 1.90 | 63.89 |

Note. Based on 1545 term loans and 6414 credit lines. Ratings are based on DealScan information. The median is 0.87 percent for term loans and it is 0.58 for credit lines.

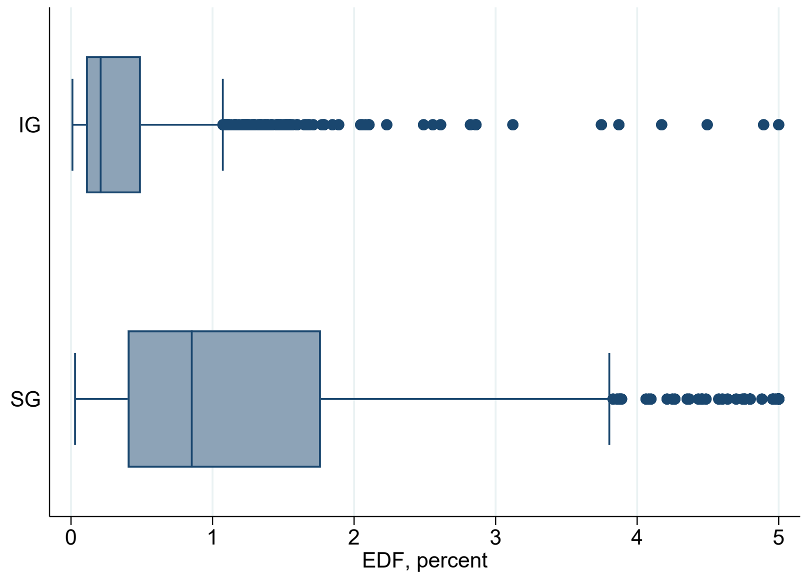


Figure 2: Distributions of EDFs of IG- and SG-rated borrowers of credit lines

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tails are abridged at 5 percent.

Basel Accord II ended their advantageous capital treatment, see Plosser and Santos (2018a).

While the share of non-bank originators has been grown, banks still originate the bulk of term loans, banks originate almost the entirety of credit lines. Lender tend to have smaller shares in term loans than in credit lines (figure 4).[6] Withing a few weeks of origination, banks sell stares in terms loans to shadow banks—institutional investors such as mutual funds or structured finance vehicles—and retain only modest shares, see Lee, Liu, and Stebunovs (2019). In contrast, banks retain credit lines in full. There are multiple explanations why banks do not follow an originate-to-distribute model for credit lines. One of them is that other types of financial intermediaries are ill-suited to deal with optionalities built in credit lines. In particular, the borrowers' option to draw at will exposes the lenders to liquidity shocks, which non-banks may not be able to handle.

As the literature suggests, credit lines have complex pricing structures because of the optionalities built into them, . Besides charging for line originations, banks charge borrowers fees and undrawn spreads (together "all-in-undrawn spreads") while lines remain unused and other fees and drawn spreads when lines are drawn (together "all-in-drawn spreads").

Berg, Saunders, and Steffen (2016) test for two main, theory-inspired purposes of the complex pricing structures. First, banks use fees and spreads to price options embedded in corporate loan contracts, in particular, the option to draw down on a credit line. (Borrowers may draw on their credit lines right at origination or any other moment or they may never use them.) At the time borrowers exercise this option, there is a value transfer from banks to borrowers: Borrowers choose

[6]In contrast to the limited availability of loan shares in DealScan for term loans, loan shares for credit lines are available for the majority of the syndicates.

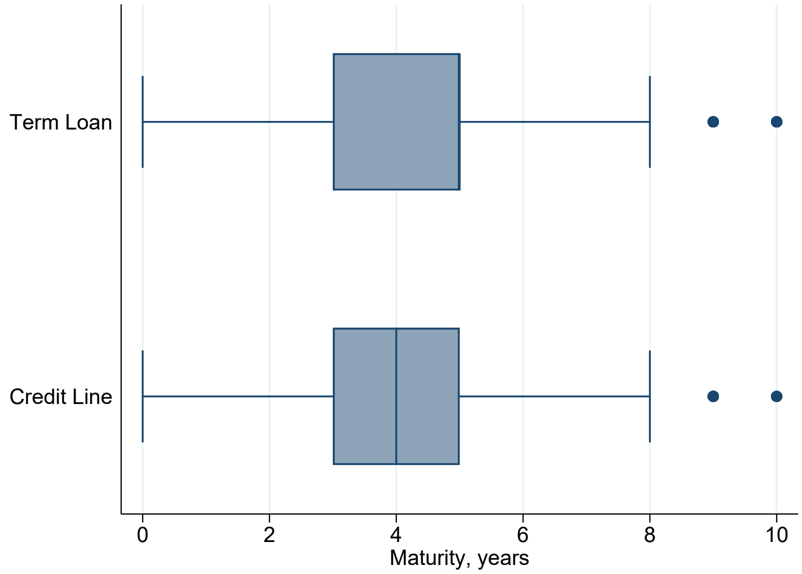


Figure 3: Distribution of loan and line maturities

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tails are abridged at 10 years.

to use the credit line if the contracted interest rate is lower than the current spot market rate. Moreover, Berg, Saunders, and Steffen (2016) show that firms are more likely to draw on their credit lines when their economic situation deteriorates: Drawdowns by borrowers with the lowest realized equity returns in the first three years post line origination are significantly higher. They also find that upfront fees and the all-in-undrawn spread are larger for high-volatility borrowers as measured by volatility of either their equity or their profitability. Second, banks use fees and spreads to screen borrowers for their private information about exercising the options embedded in a loan contract, as well as to alter ex post incentives. For example, a borrower can signal a low likelihood of future usage of a credit line by self-selecting into a contract with a high spread and a low commitment fee. Berg, Saunders, and Steffen (2016) find that borrowers that pay a lower all-in-undrawn spread and a higher all-in-drawn spread are less likely to draw on their credit line. Furthermore, average usage rates are materially lower for borrowers whose contracts specify a utilization fee that applies when a borrowers usage exceeds a specific commitment threshold. While Berg, Saunders, and Steffen (2016) do not seek to determine whether banks use fees exactly to screen borrowers or to alter their ex post incentives, they do demonstrate that loan pricing structures are clearly correlated with ex post usage of credit lines.

We document that the distributions of the all-in-undrawn and all-in-drawn spreads are sharply different (figure 5). All-in-undrawn spreads are much lower than all-in-drawn spreads. Both spreads reflect, among other things, banks' assessment of ex ante borrower credit risk. In fact, the correlation between $log(all-in-undrawn\ spread)$s and $log(EDF)$s is 0.54 and that between $log(all-in-drawn\ spread)$s and $log(EDF)$s is 0.49, both are statistically significant.

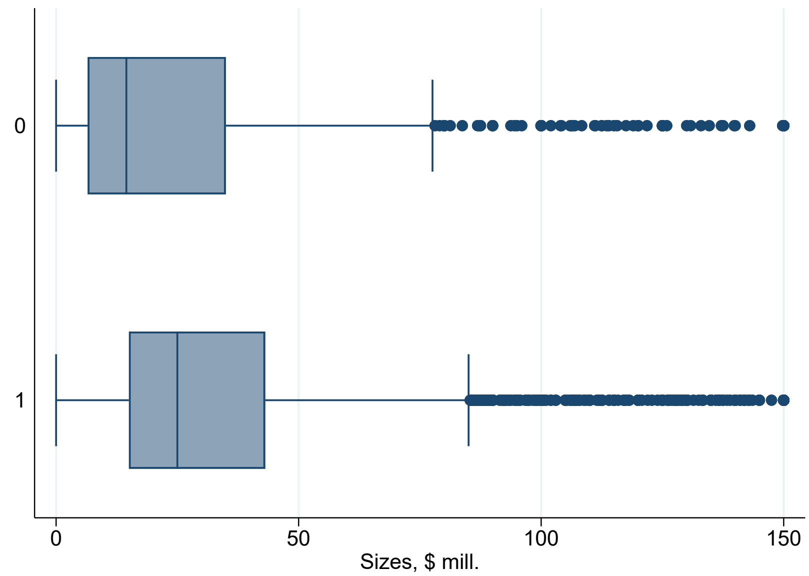


Figure 4: Distribution of shares in loans and lines

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tails are abridged at $0.15 billion.

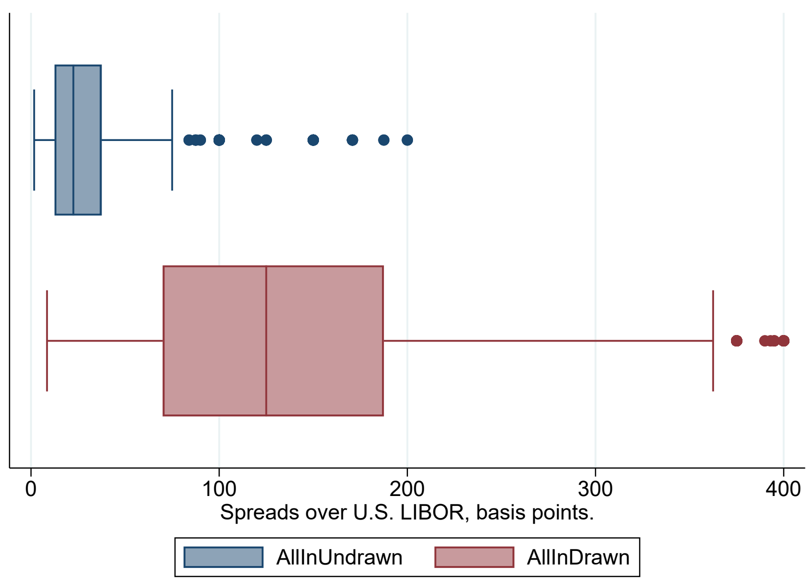


Figure 5: Distribution of all-in-undrawn and all-in-drawn spreads

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tails are abridged.

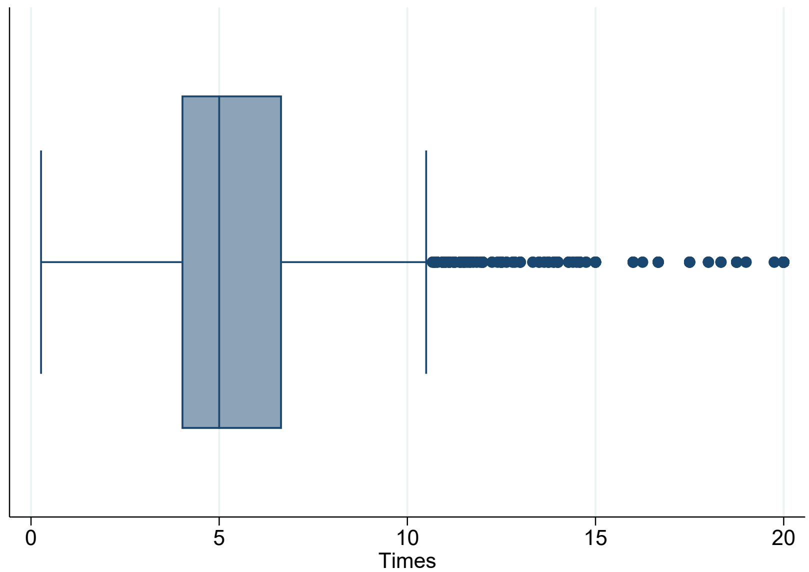


Figure 6: Distribution of the ratio of all-in-undrawn and all-in-drawn spreads ($UD$)

Note. Based on all matches of EDFs and term loans and credit lines, not just those that appear in the regressions. For charting purposes, the right tail is abridged.

Following Berg, Saunders, and Steffen (2016), for a given line, we interpret the ratio of the spreads as measuring the bank-assessed likelihood that the borrower will draw on it. We denote the ratio as $UD$, for "unlikely draw". The distribution of $UD$s has a median of 5 times and has a long right tail (figure 6). While both all-in-undrawn and all-in-drawn spreads are significantly correlated with EDFs, the ratio of the spreads ($UD$s) is not, see figure 7. Thus, $UDs$ do not reflect ex ante credit risk but rather they tell us about something else, which is, again, likelihood or disincentives to draw down credit lines.

Separately, covenants give an option for the banks to terminate or renegotiate a contract once they are breached. As Roberts and Sufi (2009)) find, over 90 percent of long-term contracts are renegotiated prior to their stated maturity and are rarely a consequence of default. The accrual of new information about the borrower's credit quality, collateral, and other conditions are the primary determinants of renegotiation.

# 4 Empirical methodology

Our empirical methodology mostly draws on the papers about a quantity-based risk-taking channel of monetary policy that operates through term loans and other banking papers. We study originations as in Dell'Ariccia, Laeven, and Suarez (2017) and many others. In contrast to typical papers on risk-taking that study credit risk of new loans, we focus on amounts of new risky lending, as in Altavilla, Boucinha, Peydro, and Smets (2019) and Lee, Liu, and Stebunovs (2020). The latter focuses on amounts of risky bilateral term loans that banks originate in response to euro-area

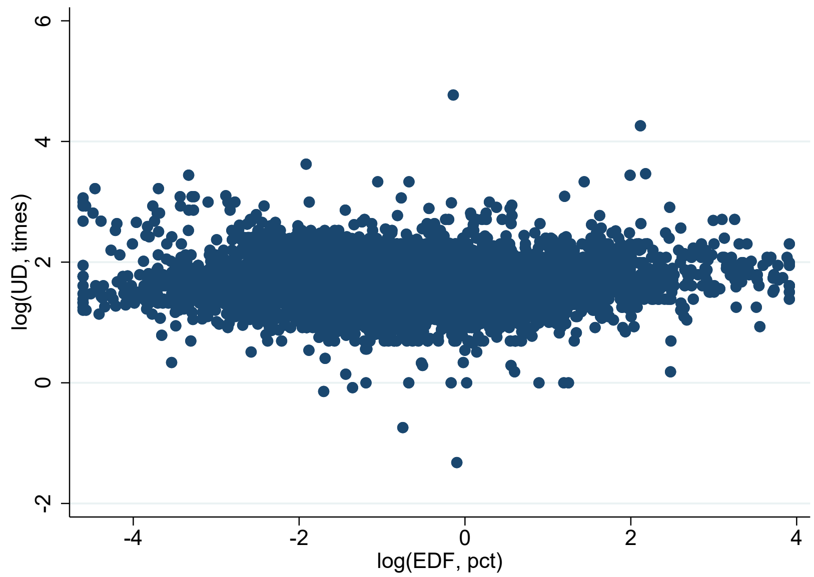


Figure 7: Scatter plot of UDs and EDFs

Note. Based on all matches of EDFs and credit lines, not just those that appear in the regressions.

policy rates. The former studies amounts of risky syndicated term loans that lenders originate in response to U.S. policy rates. It also exploits the syndication features for identification: Within a syndicate, multiple banks of different characteristics lend different amounts to the same borrower on exactly the same terms. This setup builds on Khwaja and Mian (2008) where banks of different characteristics lend to the same borrowers but not on the same terms. We then adapt Lee, Liu, and Stebunovs (2020)'s approach to capture the option-like features of credit lines. Specifically, in light of Berg, Saunders, and Steffen (2016) and other papers, we differentiate credit lines by their likelihood of being drawn. We identify the effects of monetary through interaction terms of policy rates and bank or contract terms, as in Kashyap and Stein (2000). The causal inference is further strengthened through a battery of fixed effects.

We estimate the following regression model which is semi-log with respect to U.S. policy rates and log-log with respect to the variables that capture credit risk of borrowers and likelihood of credit line drawdowns (because of the pronounced skewness of the respective distributions):

$$
\begin{aligned}
log(Line_{j,b,l,t}) &= \beta_U log(UD_{j,t}) + \beta_E log(EDF_{j,b,t}) \\
&+(\theta_{UE} log(EDF_{j,b,t}) + \theta_{UR} R_t) \times log(UD_{j,t}) \\
&+\underbrace{(\theta_{ER} + \theta_{EUR} log(UD_{j,t})) \times log(EDF_{j,b,t}) \times R_t}_{risk-taking\ channel\ of\ MP\ for\ credit\ lines} \\
&+\underbrace{\phi_{b,l} + \phi_{b,t} + \phi_{l,t}}_{fixed\ effects} + \varepsilon_{j,b,l,t}
\end{aligned} \tag{1}
$$

where $Line_{j,b,l,t}$ is bank $l$'s line $j$ (a share in a syndicated line) made to borrower $b$ at time $t$.

$EDF_{j,b,t}$ is a Moody's Analytics CreditEdge $EDF$ for borrower $b$ at a horizon that matches the maturity of loan $j$. $log(UD_{j,t}$ is a log of ratio of an all-in drawn spread and an all-in undrawn spread specified in the contract for line $j$. Notice that $log(EDF)$ is negative for $EDF$s smaller than 1 percent and positive for $EDF$s larger than 1 percent. This log feature is advantageous because it allows to separate safe and risky borrowers. As we covered earlier, the distributions of $EDFs$ by investment rating suggest that the 1 percent threshold as a cut-off that separates IG-rated and lower-rated borrowers.

Following Berg, Saunders, and Steffen (2016), we associate the ratio with a likelihood of credit line $j$ being drawn and in regression tables label it as "unlikely draw". As a reminder, a higher ratio indicates a lower likelihood of a line drawdown.

$R_t$ is a U.S. policy rate, which is the Wu and Xia (2016) shadow federal funds rate. Note that we estimate the model with the one-year Treasury constant maturity rate as well. But still our base rate is Wu and Xia (2016)'s because it captures the effects of unconventional monetary policy on interest rates and shows more time variation in the zero lower bound period.

$\phi_{b,l}$ is a fixed effect for a non-random relationship of a borrow-bank pair. As the literature suggest, banks learn credit-pertinent information from their past interactions with borrowers and incorporate this information in future decisions to supply new credit.

$\phi_{b,t}$ and $\phi_{l,t}$ are borrower-specific and bank-specific time fixed effects, respectively. Obviously, the lender- and borrower-specific time fixed effects subsume any idiosyncratic or systemic stress episodes, be it liquidity related or not.

$\varepsilon_{j,b,l,t}$s are white noise errors which we cluster by time and bank.[7]

We also examine the importance of observed bank time-varying characteristics ($CHR_{l,t}$) using the following model:

$$\begin{aligned}
log(Line_{j,b,l,t}) &= \beta_U log(UD_{j,t}) + \beta_E log(EDF_{j,b,t}) + \beta_C CHR_{l,t} \\
&+ (\theta_{UE} log(EDF_{j,b,t}) + \theta_{UR} R_t) \times log(UD_{j,t}) \\
+(\theta_{CU} log(UD_{j,t}) + \theta_{CE} log(EDF_{j,b,t}) &+ \theta_{CUE} log(UD_{j,t}) \times log(EDF_{j,b,t})) \times CHR_{l,t} \\
&+ \underbrace{(\theta_{ER} + \theta_{EUR} log(UD_{j,t})) \times log(EDF_{j,b,t}) \times R_t}_{risk-taking\ channel\ of\ MP\ for\ credit\ lines} \\
&+ \underbrace{(\theta_{CER} + \theta_{CEUR} log(UD_{j,t})) \times CHR_{l,t} \times log(EDF_{j,b,t}) \times R_t}_{bank-specific\ risk-taking\ channel\ of\ MP\ for\ credit\ lines} \\
&+ \underbrace{\phi_{b,l} + \phi_{b,t} + \phi_{l,t}}_{fixed\ effects} + \varepsilon_{j,b,l,t}
\end{aligned} \tag{2}$$

It is essentially the same model as 1 but with new interaction terms that involve observed bank characteristics.

In both models, the coefficients of interest are those on the interactions of $log(EDF)$ and $R$, see $\theta_{ER}$s in the regression models, versus the interactions of $log(EDF)$, $R$, and $log(UD)$, see $\theta_{EUR}$s.

[7] We use Correia (2016)'s estimator for linear models with multi-way fixed effects and error clustering.

$\theta_{ER}$s identify a risk-taking channel that the literature says operate through term loans. It may as well apply to credit lines. In turn, $\theta_{EUR}$s identify a part of a risk-taking channel that is specific to credit lines because they take into account the optionality built into credit lines. In the second model, the additional coefficients of interest involve observed bank characteristics. Because of the time fixed effects, some variables that appear in the interaction terms, such as $R_t$ do not appear in the models on a standalone basis.

We study only the intensive margin of contract terms on originated credit lines. Our data do not allow for study of the extensive margin, for example, of the likelihood of obtaining credit lines because we do not have data on potential borrowers that did not receive credit.

# 5 Estimation results

## 5.1 Descriptive statistics

For credit lines, we show the descriptive statistics for the sample that used in estimation of our more stringent regression model in table 2. Note that the size of the sample (nearly 50,000 observations) is smaller than the size of the merged population that underlies the figures in the earlier section (over 73,000 observations) because of the model's rich fixed effects. Some of the variables are in logs because of the pronounced skewness of their distributions. The sample includes only U.S. borrowers for multiple reasons. First, U.S. borrowers account for the overwhelming majority of orignations of credit lines. Keeping odd-duck non-U.S. borrowers in the sample introduces noise. Second, U.S. borrowers have U.S. dollar-denominated revenue and, thus, they do not expose themselves to exchange rate risk by borrowing in U.S. dollars. Despite the focus on U.S. borrowers, the split between U.S. and foreign banks by originations volume is nearly even.

Table 2: Descriptive statistics for credit lines

| | count | mean | stan. dev. | 25th pctl | 50th pctl | 75th pctl |
|---|---|---|---|---|---|---|
| log(loan share, $ bill.) | 49658 | -3.45 | 0.99 | -4.05 | -3.47 | -2.81 |
| log(EDF, pct) | 49658 | -1.10 | 1.30 | -1.92 | -1.08 | -0.27 |
| shadow int. rate, pct | 49658 | 2.57 | 2.81 | 0.38 | 2.49 | 5.26 |
| 1-y. Treasury rate, pct | 49658 | 3.02 | 2.24 | 0.59 | 2.67 | 5.36 |
| log(unlikely draw ratio, times) | 49658 | 1.61 | 0.40 | 1.39 | 1.61 | 1.83 |
| utilization fee, bps* | 13370 | 11.71 | 8.70 | 7.50 | 12.50 | 12.50 |
| cash-flow covenant dummy | 49658 | 0.61 | 0.49 | 0.00 | 1.00 | 1.00 |
| prompt corr. power, index | 47022 | 3.87 | 2.28 | 4.00 | 5.00 | 6.00 |
| fin. statement transpar., index | 48335 | 5.16 | 0.65 | 5.00 | 5.00 | 6.00 |
| loans-to-deposits ratio, pct | 26431 | 87.34 | 18.97 | 74.27 | 87.12 | 98.72 |
| Tier 1 capital ratio, pct | 26158 | 9.84 | 2.32 | 8.07 | 8.70 | 11.78 |

* For observations with non-zero utilization fees.

## 5.2 Naive take

To set a baseline and to illustrate the shortcoming of a naive approach, we estimate equation 1 without all the $UD$ terms, so $\theta_{ER}log(EDF_{j,b,t}) \times R_t$ is the only term that captures a risk-taking channel of monetary policy. We present the estimation results for both term loans and credit lines to contrast the differences in table 3. The results for term loans in column 1 are from Lee, Liu, and Stebunovs (2020) and are based on U.S. dollar-denominated term loans made to both U.S. and foreign borrowers. Because of sample size issues, it is hard to estimate such a model solely for U.S. borrowers. The results show that a (global) risk-taking channel of U.S. monetary policy operates through originations of term loans. Banks originate larger loans to risky borrowers in response to lower U.S. policy rates (because $log(EDF_{j,b,t}$s for term loans are positive and the coefficient on $\theta_{ER} log(EDF_{j,b,t}) \times R_t$ is negative and statistically significant). In contrast, the results for credit lines in columns 2 and 3 suggest a contrasting, more nuanced channel. For safer borrowers (those with negative $log(EDF_{j,b,t})$, banks originate larger lines in response to lower U.S. policy rates. But for the riskiest borrowers (those with positive $log(EDF_{j,b,t})$, banks do the opposite. Thus, on the surface, a risk-taking channel of U.S. monetary policy, does not operate through credit lines.

Table 3: Regressions for comparison of term loans and credit lines

| | (1)<br>log(Term loan) | (2)<br>log(Credit lines) | (3)<br>log(Credit lines) |
|---|---|---|---|
| log(EDF) | 0.344*** | 0.049 | 0.059 |
| | (2.649) | (0.567) | (0.689) |
| log(EDF) × **shadow int. rate** | -0.076* | 0.044** | 0.042** |
| | (-1.899) | (2.585) | (2.494) |
| Num. of observ. | 6895 | 64887 | 49658 |
| R-sq. adj. | 0.66 | 0.73 | 0.71 |
| R-sq. within adj. | . | 0.02 | 0.04 |
| RMSE | 0.65 | 0.50 | 0.54 |
| Relationship FE | N | N | Y |
| Borrower TFE | Y | Y | Y |
| Bank TFE | Y | Y | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note. Errors clustered by bank and time.

## 5.3 Drawdown optionality

As noted earlier, borrowers have an option to drawn on credit lines at will. As Berg, Saunders, and Steffen (2016) demonstrate, lenders specify a menu of spreads and fee types to price options embedded in loan contracts such as the drawdown option and use fees and spreads to screen borrowers based on the likelihood of exercising these options. To re-examine the existence of a risk-taking channel taking into account optionalities built into credit lines, we estimate equation 1 with all the terms included. We show the estimation results in table 4. The results in columns 1 and 2 are very similar despite having different fixed effects and, thus, different sample sizes. For convenience, we format the components of the interaction forms differently (underscored, bold, italics).

We focus on the two bottom rows that capture a risk-taking channel of monetary policy. As the estimates suggest the channel is nuanced in that it is different for unlikely-to-be-drawn lines made to risky, SG-rated borrowers than for other kinds of credit lines and borrowers. For risky, SG-rated borrowers, those $EDFs$ are sufficiently high for their $log(EDF)$s to be positive, an estimated risk-taking channel works as follows. The positive coefficient $\theta_{ER}$ on $log(EDF) \times R$ in the second row from the bottom points at the familiar result: Banks originate smaller lines in response to lower U.S. policy rates. However, the coefficient $\theta_{EUR}$ on $log(EDF) \times R \times log(UD)$ is negative, about half in absolute terms of $\theta_{ER}$. Thus, the sign of the overall effect on line amounts for risky borrowers of lower policy rates depends on the value of $log(UD)$. Because $UD$s are larger than one, the value of $log(UD)$ is always positive. For sufficiently high $UD$s (meaning for less likely to be drawn lines), the combination $(\theta_{ER} + \theta_{EUR} log(UD))$ is negative. Thus, overall, for risky, SG-rated borrowers, banks increase amounts of credit lines in response to lower policy rates. For safe, IG-rated borrowers, those $EDFs$ are sufficiently low for their $log(EDF)$s to be negative, the risk-taking channel operates in "reverse": Banks increase amounts of credit lines in response to higher policy rates.

Table 4: Regressions

| | (1)<br>log(Credit lines) |
|---|---|
| ***log(unlikely draw)*** | -0.405 |
| | (-1.347) |
| log(EDF) | 0.369 |
| | (1.055) |
| log(EDF) × ***log(unlikely draw)*** | -0.179 |
| | (-1.608) |
| **shadow int. rate** | 0.000 |
| | (0.000) |
| **shadow int. rate** × ***log(unlikely draw)*** | -0.036 |
| | (-0.568) |
| log(EDF) × **shadow int. rate** | 0.125* |
| | (1.741) |
| log(EDF) × **shadow int. rate** × ***log(unlikely draw)*** | -0.061** |
| | (-2.225) |
| Constant | -2.475*** |
| | (-8.393) |
| Num. of observ. | 49658 |
| R-sq. adj. | 0.71 |
| R-sq. within adj. | 0.06 |
| RMSE | 0.53 |
| Relationship FE | Y |
| Borrower TFE | Y |
| Bank TFE | Y |

$t$ statistics in parentheses
Note. Loans on an ultximm basis. The left hand side variable is lLoanStake.
All regressions have individual lender and borrower time fixed effects.
Errors clustered by lender and time.
$^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

We construct back-of-the-envelope marginal effects to illustrate the economic significance of the estimates. Because the regression model is semi-log in $R$, the overall marginal effect of a change in the policy rate on the size of credit lines, evaluated at a certain $UD$ and $EDF$ threshold, in percent is: $\Delta log(line)/\Delta R = 100 \times (\theta_{ER} + \theta_{EUR} log(UD)) \times log(EDF) \mid UD,\ EDF$. The sign of this marginal effect, in part, depends on the sign of $log(EDF)$s, which is negative for low-risk, IG-rated borrowers and positive for high risk, SG-rated borrowers. The $log(EDF)$ sign is positive for $EDF$s from about the 75th percentile its population distribution.

Figure 8 illustrates the overall effects conditional on $log(UD)$ at four percentiles, with higher percentiles associated with more unlikely-to-be-drawn credit lines. The effects are conditional the 90th percentile of the $EDF$ population distribution (which maps into a SG-rated borrower with an $EDF$ of about 2 percent). The figure shows both the estimates of the effect and their 95 percent confidence intervals. Note that with $log(UD)$ at the 75th or higher percentile, one may not reject that the overall effect is negative. With $log(UD)$ at the 95th percentile, the overall effect is

−1.1 percent. Thus, a one-standard-deviation decrease in the policy rate causes the size of risky, unlikely-to-be-drawn credit lines increase by $1.1 \times 2.8 = 3.1$ percent.

While the magnitude may not appear large and is based on the right-tail of the conditioning variables, the analysis still helps to introduce a novel channel. Banks originate larger lines to the riskiest borrowers in response to lower U.S. interest rates and they protect themselves against liquidity shocks due to these risky borrowers by reducing the likelihood of line drawdowns. That is, banks bet on credit lines to remain off their balance sheets as unfunded commitments.

Going back to the magnitude, we develop on the importance of the risk-taking channel further in the subsequent sections. We introduce additional safeguards that banks put in line contracts to insure themselves against liquidity shocks, and these safeguards further strengthen the channel. In addition, we show that channel is stronger for non-financial corporate borrowers, for a forward-looking proxy of the policy rate, and for the pre-crisis period.

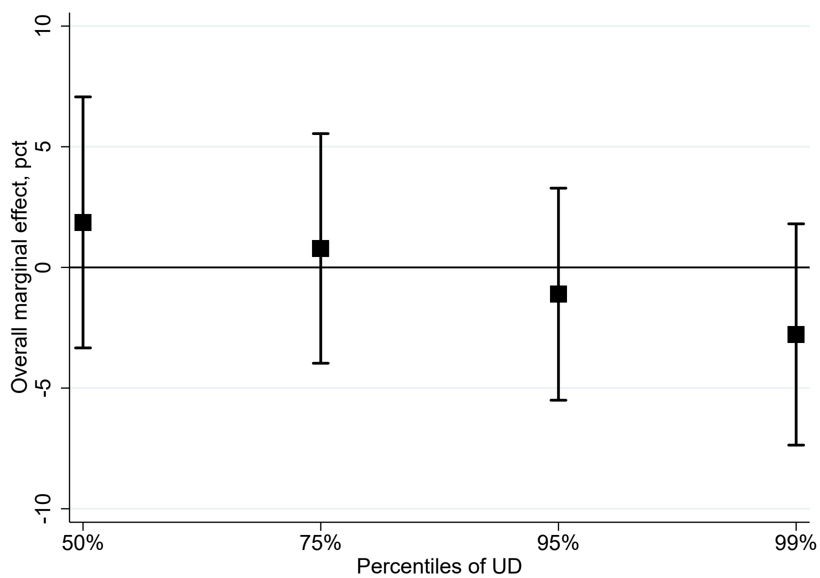


Figure 8: Overall effect of a change in the policy rate

Note. The overall marginal effect of a change in the policy rate on the size of credit lines in percent is $100 \times (\theta_{ER} + \theta_{EUR} log(UD)) \times log(EDF) \mid EDF$ at the 90th percentile of its population distribution. The figure shows both the estimates of the effect and their 95 percent confidence intervals.

## 5.4 Cash-flow safeguards

Banks can use multiple approaches to reduce the likelihood of drawdowns, with making drawdowns costly being just one of them. Banks can and tend to impose in line contracts cash-flow covenants that force the borrowers to maintain ample cash flows to cover various debt-related expenditures, for example debt-to-EBITDA and debt service coverage covenants. It may well be that these multiple approaches are complementary.

To check whether cash-flow safeguards play a role and whether they complement the pricing-based protection against drawdowns, we again rely on equation 4. However, we modify it slightly and re-estimate it separately for each of three new variables. First, replace $log(UD_{j,t})$ with a dummy that is equal to one if an value of $log(UD_{j,t})$ is in the 75th or higher percentile (the range where a risk-taking channel exists, as we described in the preceding section) and is equal to zero otherwise. Then we re-estimate the regression model, with the results shown in column 1 in table 5. The bottom two rows confirm the earlier, familiar finding that banks originate larger lines to the riskiest borrowers in response to lower policy rates when they do not anticipate line drawdowns.

Next, we define a cash-flow covenant dummy as follows. For a given line, it is equal to one if at least on the following covenant is present in the contract: EBITDA, cash interest coverage, debt service coverage, interest coverage, fixed charge coverage, debt to EBITDA, or senior debt to EBITDA. It is equal to zero otherwise. Then, we re-estimate the model with the cash-flow covenant dummy. The results in column 2 suggest that the overall effect on lower policy rates on the sizes of risky credit lines with cash-flow safeguards is zero (the two coefficients of interest in the bottom two rows are of opposite signs and of similar magnitude in absolute terms).

Finally, we examine the complementary possibility. We construct a new dummy that is equal to one if both the unlikely-to-draw-dummy and the cash-flow covenant dummy are equal to one. The new dummy is equal to zero otherwise. Then we re-estimate the model with this combination dummy. The results in column 3 (the bottom two rows) suggest that the two approaches to reduce drawdowns may be complementary as they re-enforce the strength of the risk-taking channel (the sum of the two coefficients in the bottom rows is much larger in magnitude in absolute terms than that for column 1) .

Table 5: Regressions for cash-flow safeguards

| | (1)<br>Unlikely draw dummy | (2)<br>Cash-flow covenant dummy | (3)<br>Combination dummy |
|---|---|---|---|
| dummy | 0.305 | 0.972** | 0.351 |
| | (1.240) | (2.242) | (1.044) |
| log(EDF) | -0.029 | -0.079 | -0.054 |
| | (-0.252) | (-0.683) | (-0.509) |
| log(EDF) × dummy | 0.043 | 0.361*** | 0.245* |
| | (0.398) | (2.828) | (1.932) |
| **shadow int. rate** × dummy | -0.086 | -0.005 | -0.117* |
| | (-1.604) | (-0.056) | (-1.883) |
| log(EDF) × **shadow int. rate** | 0.062*** | 0.065*** | 0.066*** |
| | (2.852) | (2.850) | (3.226) |
| log(EDF) × **shadow int. rate** × dummy | -0.086** | -0.062** | -0.164*** |
| | (-2.129) | (-2.313) | (-3.610) |
| Num. of observ. | 49658 | 49658 | 49658 |
| R-sq. adj. | 0.71 | 0.71 | 0.71 |
| R-sq. within adj. | 0.05 | 0.04 | 0.06 |
| RMSE | 0.53 | 0.53 | 0.53 |
| Relationship FE | Y | Y | Y |
| Borrower TFE | Y | Y | Y |
| Bank TFE | Y | Y | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note. Errors clustered by bank and time.

We note that the two types of mitigants complement each other in part because they appear in contracts for borrowers from distinct industries. As table 6 shows, the occurrences of unlikely-to-be-drawn lines and cash-flow covenant lines are not materially correlated across the 12 Fama-French industries. Some industries have high occurrences of unlikely-to-be-drawn lines and low occurrences of cash-flow covenant lines, vice versa, or have occurrences that are either both low or high. For example, finance has the highest occurrence of unlikely-to-be-drawn lines and one the lowest occurrences of cash-flow covenant lines. In contrast, wholesale and retail trade and other services have one of the lowest occurrences of unlikely-to-be-drawn lines and the highest occurrence of cash-flow covenant lines. Utilities have occurrences that are both low. (We do not explore the reasons for these differences in occurrences, which likely reflect industry characteristics.) Importantly, the simultaneous occurrences of the unlikely-to-be-drawn pricing and cash-flow covenants are not concentrated in a small subset of the industries (column 3). In fact, all the industries with exception of utilities and oil, gas, and coal extraction have roughly similarly simultaneous occurrences of the unlikely-to-be-drawn pricing and cash-flow covenants. Thus, we attribute the results in column 3 in table 5 to a wide range of industries.[8]

Table 6: Occurencies of unlikely-to-be-drawn lines and of cash-flow covenant lines

| Industry | Number of lines | Percentage frequency of lines | | |
|---|---|---|---|---|
| | | Unlikely to be drawn | Cash-flow covenants | Both |
| Business Equipment | 625 | 37 | 70 | 24 |
| Healthcare | 350 | 31 | 79 | 22 |
| Consumer Non-durables | 451 | 27 | 74 | 21 |
| Wholesale, Retail, and Services | 862 | 27 | 76 | 20 |
| Chemicals | 205 | 27 | 69 | 20 |
| Finance | 956 | 40 | 55 | 19 |
| Mines, Construction, and others | 869 | 31 | 72 | 19 |
| Manufacturing | 860 | 26 | 72 | 17 |
| Telecommunication | 201 | 24 | 71 | 17 |
| Consumer Durabless | 183 | 39 | 57 | 15 |
| Utilities | 466 | 33 | 36 | 11 |
| Oil, Gas, and Coal Extraction | 547 | 23 | 64 | 9 |

Note. Based on the Fama-French 12 industry classification.

We construct back-of-the-envelope marginal effects to illustrate the economic significance of the estimates yet again. Because the regression model is semi-log in $R$, so the overall marginal effect of a change in the policy rate on the size of credit lines, evaluated at a certain $UD$ and $EDF$ threshold, in percent is: $\Delta log(line)/\Delta R = 100 \times (\theta_{ER} + \theta_{EUR} dummy) \times log(EDF) \mid dummy,\ EDF$. As earlier, the sign of this marginal effect, in part, depends on the sign of $log(EDF)$s, which is negative for low-risk, IG-rated borrowers and positive for high risk, SG-rated borrowers. In column 1, the marginal overall effect, conditional on $EDF$ at the 90th percentile of its population distribution, is $-1.66$ percent. Thus, a one-standard-deviation decrease in the policy rate causes the size of risky, unlikely-to-be-drawn credit lines increase by $1.66 \times 2.8 = 4.65$ percent. In column 3, which captures the effects of discouragement to draw the line and cash-flow safeguards, the overall marginal effect is $-7.07$ percent. Thus, a one-standard-deviation decrease in the policy rate causes the size of risky, unlikely-to-be-drawn credit lines increase by $7.07 \times 2.8 = 19.8$ percent. As advertised earlier, the economic significance of these estimates is much higher than that of the estimates in table 4.

[8] While it is unlikely that borrowers from finance, who are mainly real estate investment trusts and insurance companies, drive the results, we do a robustness check where we exclude such borrowers from the analysis.

## 5.5 Bank characteristics

In this section, we examine the importance of bank characteristics to strength the evidence on the nature of the risk-taking channel. In particular, we aim to demonstrate the importance of banks' access to liquidity for the existence and strength of the channel. Because line drawdowns are liquidity shocks to banks, banks with better access to U.S. dollar liquidity may engage in risk-taking in response to lower interest rates more aggressively. We also examine whether the strength of banks' capital positions affect their risk-taking behavior. For term loans, the literature documents that banks with stronger capital positions take on more ex ante credit risk in response to lower policy rates than banks with weaker capital positions (for example, Dell'Ariccia, Laeven, and Suarez (2017) and Lee, Liu, and Stebunovs (2019)).

Table 7: Regressions for bank characteristics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Characteristic: | Foreign | Supervision | Transparency | Loans-to-dep. | Tier 1 capital |
| Unlik. draw d. | 0.316 | 0.322 | 0.224 | 0.462* | 0.291 |
| | (1.293) | (1.338) | (0.564) | (1.767) | (0.815) |
| $\underline{\text{log(EDF)}}$ | -0.013 | -0.044 | -0.142 | -0.058 | -0.034 |
| | (-0.117) | (-0.325) | (-0.739) | (-0.594) | (-0.125) |
| $\underline{\text{log(EDF)}}$ × Unlik. draw d. | 0.038 | 0.119 | 0.258 | 0.107 | 0.252 |
| | (0.354) | (1.011) | (1.129) | (0.929) | (1.106) |
| Char. | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Char. × Unlik. draw d. | -0.013 | -0.006 | 0.017 | -0.000 | 0.022 |
| | (-0.364) | (-0.441) | (0.282) | (-0.300) | (0.701) |
| **shd int. rate** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| **shd int. rate** × Unlik. draw d. | -0.094* | -0.083 | -0.113 | -0.025 | -0.238* |
| | (-1.766) | (-1.599) | (-1.302) | (-0.345) | (-1.934) |
| Char. × $\underline{\text{log(EDF)}}$ | -0.028* | 0.006 | 0.021 | 0.000 | -0.000 |
| | (-1.817) | (0.996) | (0.986) | (0.904) | (-0.013) |
| Char. × $\underline{\text{log(EDF)}}$ × Unlik. draw d. | 0.014 | -0.013 | -0.036 | -0.000 | -0.008 |
| | (0.613) | (-1.477) | (-1.026) | (-0.156) | (-0.414) |
| $\underline{\text{log(EDF)}}$ × **shd int. rate** | 0.059*** | 0.062** | 0.086** | 0.051** | 0.079 |
| | (2.737) | (2.470) | (2.282) | (2.562) | (1.306) |
| $\underline{\text{log(EDF)}}$ × **shd int. rate** × Unlik. draw d. | -0.074* | -0.113*** | -0.210*** | 0.003 | -0.230** |
| | (-1.965) | (-2.643) | (-3.156) | (0.078) | (-2.244) |
| Char. × **shd int. rate** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Char. × **shd int. rate** × Unlik. draw d. | 0.018 | -0.001 | 0.005 | -0.001*** | 0.013 |
| | (1.576) | (-0.447) | (0.329) | (-3.113) | (0.894) |
| Char. × $\underline{\text{log(EDF)}}$ × **shd int. rate** | 0.005* | -0.000 | -0.005 | 0.000 | -0.002 |
| | (1.709) | (-0.414) | (-1.055) | (1.140) | (-0.317) |
| Char. × $\underline{\text{log(EDF)}}$ × **shd int. rate** × Unlik. draw d. | -0.017*** | 0.006*** | 0.024** | -0.001** | 0.018* |
| | (-2.722) | (2.863) | (2.499) | (-2.154) | (1.724) |
| Num. of observ. | 49658 | 46711 | 48179 | 24246 | 23920 |
| R-sq. adj. | 0.71 | 0.71 | 0.71 | 0.65 | 0.64 |
| R-sq. within adj. | 0.05 | 0.05 | 0.05 | 0.02 | 0.03 |
| RMSE | 0.53 | 0.53 | 0.53 | 0.57 | 0.57 |
| Relationship FE | Y | Y | Y | Y | Y |
| Borrower TFE | Y | Y | Y | Y | Y |
| Bank TFE | Y | Y | Y | Y | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note. Errors clustered by bank and month.

To tackle these issues, we estimate equation 2 first with a dummy for foreign banks, then with variables that capture supervision and market discipline that banks face, with the ratio of loans to deposits, and, finally, with the Tier 1 capital ratio. We show the estimation results in table 7.

The results in column 1 show that foreign banks engage more in risk-taking in response to lower U.S. policy rates than their U.S. peers (the bottom two rows). One the one hand, one would expect that foreign banks have more limited access to U.S. dollar liquidity than U.S. banks and, thus, would engage less in such risk-taking. On the other hand, foreign banks may face weaker supervision and market discipline than their U.S. counterparts, and, thus, engage more in risk-taking.[9] To make this point, we estimate the model with Barth, Caprio, and Levine (2013)'s indexes for the strength of bank supervisors' prompt corrective power and the degree of bank reporting transparency. The estimation results in columns 2 and 3 indeed suggest that stronger supervision and more transparent reporting curbs risk-taking.

Next we examine the importance of bank liquidity and capital characteristics. First, we estimate the model with the loans-to-deposit ratio to capture banks' ability to fund drawdowns with (stable) internal liquidity (that is, deposit liabilities) rather than (fickle) wholesale funding. This check is in part inspired by the findings in Ivashina and Scharfstein (2010) that, following the he failure of Lehman Brothers in September 2008, banks cut their lending less if they had better access to deposit financing and thus, they were not as reliant on short-term debt. Second, we estimate the model with the Tier 1 capital ratio to measure banks' ability to cope with an increase in assets due to drawdowns. The results in columns 4 and 5 are very preliminary at the moment, in part because of the limited sample sizes (we have not yet matched a sufficiently large number of lenders in DealScan and Capital IQ.) The estimates in the two bottom rows hint that internal liquidity may have no effect on risk-taking, while stronger capital positions may damp it. We also examine other bank characteristics, such as the ratio of liquid assets (cash and short-term interest bearing assets) to total assets. But we cannot reliably estimate our regression models that require a higher number of observations on small samples.

## 5.6 Stability of the channel

While some pre-financial crisis papers argue that banks have a unique ability to provide liquidity support to corporations in a systemic stress evemt, more recent, post-crisis papers question the extent of this ability.

Recall that Gatev and Strahan (2006) argue that deposit inflows into banks (in part driven by implicit government support for banks during crises) provide funding for loan demand shocks that follow declines in market liquidity. They then conclude that banks can insure firms against systematic declines in liquidity at lower cost than other institutions and meet loan demand from borrowers without running down their holdings of liquid assets. This reasoning suggest that banks may not worry about borrowers drawing credit lines en masse in a systemic stress. However, our results suggest that banks care about idiosyncratic drawdowns of credit lines, let alone systemic drawdowns. (From the previous section, we know that banks that rely more on "internal" funds

[9]Other possibilities include profitability pressures: Non-U.S. banks have been notoriously significantly less profitable than their U.S. competitors, in particular, in post the financial crisis. We also note that foreign banks in our sample do not necessarily have more limited access to U.S. dollar liquidity. For example, Canadian banks, which originate a material mass of credit lines to U.S. corporates, have large U.S. subsidiaries, with robust U.S. dollar deposits.

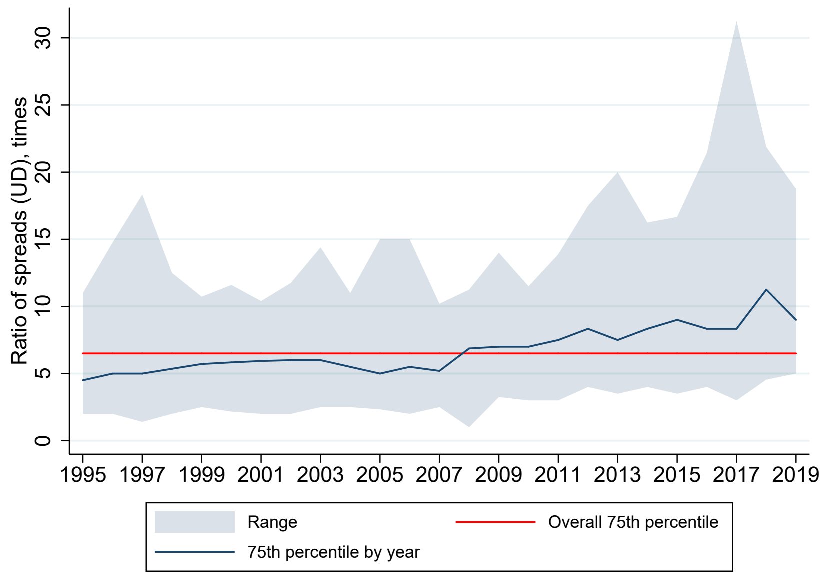


Figure 9: Distribution of the ratio of the spreads ($UD$) over time

Note. The range captures the 1st and 99th percentiles.

may engage less in originations of risky credit lines.)

Given that Gatev and Strahan (2006) predates the 2007-09 financial crisis, one easy check for the differences in the narratives is to re-estimate equation 2 with a dummy for the post-crisis period that is equal to one for the 2007-19 period.[10] We show the estimation results in table 8. They suggest the risk-taking channel operated before the crisis and that it has weakened in its aftermath. (The positive, statistically significant coefficient on the interaction of the post-crisis dummy, log(EDF), and the shadow interest rate offsets the negative, statistically significant coefficient on the interaction of log(EDF), the shadow interest rate, and the unlikely-to-draw dummy).

It may be that, following the 2007-09 financial crisis, banks have become more cognizant of liquidity and capital risks that drawdowns of credit lines present. As figure **?** shows, the distributions of the spreads of the ratios ($UD$s) have creped up since the crisis, as banks have strengthened the deterrent for borrowers to draw credit lines. It may be that banks learned that in a systemic stress their own funding may dry up and that market discipline may force them to hold large quantities of high-quality liquid assets. After all, Berrospide, Meisenzahl, and Sullivan (2012) document that, heading into the crisis, the surge in drawdowns occurred precisely when disruptions in bank funding markets began. More generally, Acharya, Almeida, and Campello (2013) find that, in times of heightened aggregate volatility, banks exposed to undrawn credit lines become riskier. Furthermore, the evidence in Acharya and Mora (2015) cast strong doubts about banks' advantage as liquidity providers in a financial crisis: While banks honored drawdowns of credit lines during the financial crisis, this liquidity provision was only possible because of explicit, large support from

[10]Acharya and Mora (2015) and many others peg the beginning of the crisis to 2007 or mid-2007.

Table 8: Regressions with a dummy for the post-crisis period

| | (1)<br>Post-crisis dummy |
|---|---|
| Unlikely draw dummy | 0.876*** |
| | (3.312) |
| $\underline{\log(\text{EDF})}$ | 0.050 |
| | (0.204) |
| $\underline{\log(\text{EDF})}$ × Unlikely draw dummy | 0.711*** |
| | (4.277) |
| Post-GFC dummy× Unlikely draw dummy | -0.519 |
| | (-1.245) |
| **shadow int. rate** × Unlikely draw dummy | -0.218*** |
| | (-4.090) |
| Post-GFC dummy × $\underline{\log(\text{EDF})}$ | 0.104 |
| | (0.361) |
| Post-GFC dummy× $\underline{\log(\text{EDF})}$ × Unlikely draw dummy | -0.745*** |
| | (-3.077) |
| $\underline{\log(\text{EDF})}$ × **shadow int. rate** | 0.046 |
| | (0.990) |
| $\underline{\log(\text{EDF})}$ × **shadow int. rate** × Unlikely draw dummy | -0.245*** |
| | (-4.526) |
| Post-GFC dummy × **shadow int. rate** × Unlikely draw dummy | 0.070 |
| | (0.480) |
| Post-GFC dummy × $\underline{\log(\text{EDF})}$ × **shadow int. rate** | 0.151* |
| | (1.754) |
| Post-GFC dummy × $\underline{\log(\text{EDF})}$ × **shadow int. rate** × Unlikely draw dummy | 0.134 |
| | (1.166) |
| Num. of observ. | 49658 |
| R-sq. adj. | 0.72 |
| R-sq. within adj. | 0.06 |
| RMSE | 0.53 |
| Relationship FE | Y |
| Borrower TFE | Y |
| Bank TFE | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note. The post-crisis period is from 2009. Errors clustered by bank and month.

the government and governmentsponsored agencies.[11] At the onset of the crisis, deposit inflows into banks weakened and their loantodeposit shortfalls widened, especially at banks with greater undrawn commitments.

And more recently, the introduction of the liquidity coverage ratio (LCR) requirements have apparently made banks' liquidity management more conservative. The LCR requirements set a minimum proportion of highly quality, highly liquid assets that banks must hold to ensure their ability to meet their short-term obligations.[12] Yankov (2020) documents that, in contrast to smaller banks that are not subject to the LCR, large U.S. banks subject to the LCR increased dramatically their holdings of high-quality liquid assets to match their liquidity risks including those that stem from providing credit lines. Relatedly, Roberts, Sarkar, and Shachar (2018) find that banks subject to the LCR create less liquidity per dollar of assets in the post-LCR period than banks that are not subject to the LCR by, in part, lending less.

# 6 Robustness checks

We offer a few robustness checks. First, we focus on the sample of credit lines originated for non-financial corporations. Banks may treat financial corporations, which account for a material percentage of the observations, differently from non-financial corporations. Financial corporations may have different uses for credit lines and may face different trade-offs when managing liquidity risks. For example, Yankov (2020) documented that, in the post-crisis period, publicly traded non-bank financial firms decreased their liquid asset holdings and increased their reliance on bank credit lines, but non-financial firms did not. This difference may imply that the two types of firms indeed faced different trade-offs. Moreover, bank surely internalize the differences in regulatory treatment of credit lines that they originate for non-financial and financial corporations.[13] We show the results in table 9. The results are very similar to those for the broader sample.

Second, we use the one-year Treasury constant maturity rate from the Federal Reserve's statistical release H.15 "Selected Interest Rates" instead of Wu and Xia (2016)'s shadow interest rate. While the shadow rate is a useful construct for carrying the analysis over a long time that includes a period of unconventional monetary policy, it may be of somewhat limited direct relevance for banks because they neither charge this rate on lend or pay it for short-term borrowing. In addition, banks may base their risk-taking decisions on an expected path of interest rates. For example,

[11]AsCarlson and Rose (2017) note, it is not clear the extent to which the discount window continues to suffer from stigma. However it is very likely that stigma remains a problem. Indeed, Federal Reserve Board Vice Chairman Fischer (2016) Fischer stated that he suspected stigma was even higher in the post-crisis period, given the public's incorrect association of the discount window with "bailouts."

[12]Per Yankov (2020), the LCR distinguishes between two types of credit linescredit facilities and liquidity facilities. Credit facilities are used for general corporate purposes such as funding working capital or investment expenditures. The LCR requires that every dollar of unused credit facility be backed with 10 cents of high quality liquid assets for non-financial firms and 40 cents for non-bank financial firms. Liquidity facilities are contractually designed to serve primarily as a liquidity management tool, such as to back-up issuances of commercial paper or other market debt. The LCR imposes a 100 percent outflow assumption on such liquidity facilities to non-bank financials, whereas liquidity facilities to non-financial firms require only 30 cents of high quality liquid assets for every dollar of undrawn credit line.

[13]For example, see the earlier footnote about the LCR requirements.

Table 9: Regressions for non-financial corporate borrowers

| | (1) Naive approach | (2) Unlikely draw | (3) Unlikely draw dummy |
|---|---|---|---|
| log(EDF) | 0.053 | 0.453 | 0.050 |
| | (0.599) | (1.216) | (0.396) |
| log(EDF) × **shadow int. rate** | 0.044** | 0.137* | 0.048** |
| | (2.512) | (1.782) | (2.042) |
| ***log(unlikely draw)*** | | -0.701** | |
| | | (-2.346) | |
| log(EDF) × ***log(unlikely draw)*** | | -0.240** | |
| | | (-2.033) | |
| **shadow int. rate** × ***log(unlikely draw)*** | | -0.043 | |
| | | (-0.657) | |
| log(EDF) × **shadow int. rate** × ***log(unlikely draw)*** | | -0.069** | |
| | | (-2.368) | |
| Unlikely draw dummy | | | -0.056 |
| | | | (-0.196) |
| log(EDF) × Unlikely draw dummy | | | -0.089 |
| | | | (-0.726) |
| **shadow int. rate** × Unlikely draw dummy | | | -0.051 |
| | | | (-0.721) |
| log(EDF) × **shadow int. rate** × Unlikely draw dummy | | | -0.078* |
| | | | (-1.800) |
| Num. of observ. | 41867 | 41867 | 41867 |
| R-sq. adj. | 0.70 | 0.71 | 0.70 |
| R-sq. within adj. | 0.04 | 0.07 | 0.05 |
| RMSE | 0.55 | 0.55 | 0.55 |
| Relationship FE | Y | Y | Y |
| Borrower TFE | Y | Y | Y |
| Bank TFE | Y | Y | Y |

$t$ statistics in parentheses. $^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$.
Note. Errors clustered by bank and time.

Aramonte, Lee, and Stebunovs (2019) find that, over the zero-lower-bound period, banks engaged in risk-taking in the market for syndicated term loans more when the spot or forward 10-year Treasury rate or the expected, OIS-based federal funds rate declined or the expected duration and severity of the zero-lower-bound period increased. In our case, the one-year Treasury rate captures a market-expected path of policy rate over the coming year. We show the results in table 10 in appendix. The results are similar to those based on the shadow rate, albeit they suggest a stronger risk-taking channel of monetary policy that operates through unlikely-to-be-drawn credit lines. (Because the coefficient on the interaction of $log(EDF)$ and the Treasury rate is not statistically significant, the risk-taking channel operates solely through unlikely-to-be-drawn credit lines.)

Third, in light of Berg, Saunders, and Steffen (2016)'s results that suggest that a low ratio of the spreads and the utilization fee are substitutes (because borrowers who face a high ratio or pay a utilization fee are less likely to draw on their credit lines), we reestimate equation 1 with the utilization fee. While we can construct the ratios for all credit lines, only 13 percent of observations have such a utilization fee. So, we focus on the ratios in the main analysis and relegate the analysis of the utilization fee to robustness checks, with the estimation results shown in table 11. Column 1 shows the results for utilization fees in decimals. The mean utilization fee is 3.15 basis points for the entire sample and it is 11.75 basis points for the observations with non-zero fees. The results suggest that the risk-taking channel operates for the riskiest credit lines with high utilization fees. Column 2 shows the results for a dummy that is equal to one if a utilization fee is in the 75th or higher percentile of the distribution of non-zero utilization fees and is equal to zero otherwise.

Table 10: Regressions for an alternative, expected policy rate (one-year Treasury rate)

| | (1)<br>Naive approach | (2)<br>Unlikely draw | (3)<br>Unlikely draw dummy |
|---|---|---|---|
| log(EDF) | 0.004 | 0.280 | -0.082 |
| | (0.035) | (0.674) | (-0.571) |
| log(EDF) × **1-y. Treasury rate** | 0.052** | 0.147 | 0.070** |
| | (2.384) | (1.636) | (2.579) |
| ***log(unlikely draw)*** | | -0.231 | |
| | | (-0.644) | |
| log(EDF) × ***log(unlikely draw)*** | | -0.099 | |
| | | (-0.750) | |
| **1-y. Treasury rate** × ***log(unlikely draw)*** | | -0.080 | |
| | | (-1.025) | |
| log(EDF) × **1-y. Treasury rate** × ***log(unlikely draw)*** | | -0.081** | |
| | | (-2.113) | |
| Unlikely draw dummy | | | 0.417 |
| | | | (1.448) |
| log(EDF) × Unlikely draw dummy | | | 0.168 |
| | | | (1.272) |
| **1-y. Treasury rate** × Unlikely draw dummy | | | -0.120* |
| | | | (-1.866) |
| log(EDF) × **1-y. Treasury rate** × Unlikely draw dummy | | | -0.123** |
| | | | (-2.271) |
| Num. of observ. | 49658 | 49658 | 49658 |
| R-sq. adj. | 0.71 | 0.71 | 0.71 |
| R-sq. within adj. | 0.04 | 0.06 | 0.05 |
| RMSE | 0.54 | 0.53 | 0.53 |
| Relationship FE | Y | Y | Y |
| Borrower TFE | Y | Y | Y |
| Bank TFE | Y | Y | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ .
Note. Errors clustered by bank and time.

They point at the risk-taking channel too.

Fourth, we examine potential differences in risk-taking across the maturities of credit lines, in part because of lighter capital treatment of short-term credit lines. As Plosser and Santos (2018a) explore, under the Basel I Accord, banks had to set aside capital for credit lines with maturities in excess of one year but not for short-term credit lines. The Basel II Accord extended capital requirements to most short-term commitments. Following the passage of Basel II in 2004, both undrawn fees and spreads went up, confirming that banks act to conserve regulatory capital by modifying the cost and supply of credit. In the data, we note that short-term credit lines accounted for a large share of all credit lines being originate prior Basel II and only a small share afterwards. We reestimate the equation with a dummy that is equal to one if the maturity of credit line is shorter than one year (so called "364-day facility") and that is equal to zero otherwise. (This approach may appear to encompass a test for the importance of the LCR requirements that vary by maturity of credit lines (see the earlier footnotes. However, it is effective not because the percentage of 364-day facilities post 2004 is small and the LCR requirements are new, the percentage of the observations that 364-day facilities account for in the LCR period is immaterial.) We show the estimation results in table 12. They suggest that our general results are not due to such short-term credit lines.

Table 11: Regressions for another deterrent of drawdowns (utilization fees)

| | (1) log(Credit lines) | (2) log(Credit lines) |
|---|---|---|
| log(EDF) | 0.031 | 0.036 |
| | (0.353) | (0.414) |
| log(EDF) × **shadow int. rate** | 0.054*** | 0.051*** |
| | (3.150) | (2.978) |
| Util. fee | 0.006 | |
| | (0.251) | |
| log(EDF) × Util. fee | 0.023*** | |
| | (3.099) | |
| **shadow int. rate** × Util. fee | -0.013** | |
| | (-2.067) | |
| log(EDF) × **shadow int. rate** × Util. fee | -0.008*** | |
| | (-3.290) | |
| Util. fee dummy | | 0.112 |
| | | (0.365) |
| log(EDF) × Util. fee dummy | | 0.245 |
| | | (1.132) |
| **shadow int. rate** × Util. fee dummy | | -0.149** |
| | | (-2.134) |
| log(EDF) × **shadow int. rate** × Util. fee dummy | | -0.080* |
| | | (-1.820) |
| Num. of observ. | 49658 | 49658 |
| R-sq. adj. | 0.71 | 0.71 |
| R-sq. within adj. | 0.05 | 0.05 |
| RMSE | 0.53 | 0.53 |
| Relationship FE | Y | Y |
| Borrower TFE | Y | Y |
| Bank TFE | Y | Y |

$t$ statistics in parentheses. $^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$ .
Note. Errors clustered by bank and time.

# 7 Conclusions and implications

We shed light on the existence and nature of a risk-taking channel of U.S. monetary policy that operates through bank that originate credit lines to U.S. corporations. We show that this channel exists for the riskiest borrowers and is more nuanced than that for term loans because of optionalities built into credit lines. The borrowers' key option to draw on credit line at will exposes banks to both liquidity shocks and capital shocks. Taking into account the optionality, we find that banks originate larger credit lines to the ex ante riskiest borrowers in response to lower U.S. policy rates when they structure the pricing of these lines to discourage their usage. That is, banks bet on these lines to remain off their balance sheets as unfunded commitments. Such a response is more pronounced for contracts that include cash-flow safeguards and for banks that face weaker supervision and market discipline. The response appears to be less pronounced for banks with stronger capital positions. The response of banks with stronger liquidity positions is uncertain, a finding that possibly reflects a relatively limited sample size and certainly deserves further investigation.

Because of the market and data features, our analysis is for syndicated credit lines that mostly large banks originate for relatively large U.S. corporations. Our findings may not necessarily apply to bilateral credit lines that banks originate to smaller U.S. corporations for a few reasons. First, some small corporations may not have access to credit lines at all. Second, small corporations may have more limited alternatives to credit lines and they likely manage their liquidity differently

Table 12: Regressions with a dummy for short-term credit lines

| | (1)<br>log(credit line) |
|---|---|
| Unlikely draw dummy | 0.676** |
| | (2.462) |
| $\underline{\text{log(EDF)}}$ | -0.416 |
| | (-1.482) |
| $\underline{\text{log(EDF)}}$ × Unlikely draw dummy | 0.189 |
| | (1.170) |
| 364-day facility dummy | -0.134 |
| | (-0.883) |
| 364-day facility dummy × Unlikely draw dummy | -0.461* |
| | (-1.757) |
| **shadow int. rate** × Unlikely draw dummy | -0.125** |
| | (-2.026) |
| 364-day facility dummy × $\underline{\text{log(EDF)}}$ | 0.130 |
| | (0.946) |
| 364-day facility dummy × $\underline{\text{log(EDF)}}$ × Unlikely draw dummy | -0.185 |
| | (-1.060) |
| $\underline{\text{log(EDF)}}$ × **shadow int. rate** | 0.164*** |
| | (2.877) |
| $\underline{\text{log(EDF)}}$ × **shadow int. rate** × Unlikely draw dummy | -0.116* |
| | (-1.934) |
| 364-day facility dummy × **shadow int. rate** | -0.020 |
| | (-0.619) |
| 364-day facility dummy × **shadow int. rate** × Unlikely draw dummy | 0.075 |
| | (1.157) |
| 364-day facility dummy × $\underline{\text{log(EDF)}}$ × **shadow int. rate** | -0.057* |
| | (-1.964) |
| 364-day facility dummy × $\underline{\text{log(EDF)}}$ × **shadow int. rate** × Unlikely draw dummy | 0.044 |
| | (0.843) |
| Num. of observ. | 49658 |
| R-sq. adj. | 0.72 |
| R-sq. within adj. | 0.06 |
| RMSE | 0.53 |
| Relationship FE | Y |
| Borrower TFE | Y |
| Bank TFE | Y |

$t$ statistics in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.
Note. Errors clustered by bank and time.

than larger corporations. Thus, for smaller corporations, the patterns of drawdown of credit lines may be quite different as well. Third, these differences, in turn, will affect banks' line origination strategies.

We suggest that, after a prolonged period of low interest rates, some banks that originated ex ante riskier but unlikely-to-be-drawn credit lines may be less prepared to handle en masse drawdowns in a systemic stress episode, such as a pandemic-triggered crisis. Stress in these banks could have financial stability implications, and it could lead to a cutback in the supply of credit to the broader economy.

While not focusing per se on the risk of credit lines that were originated pre-pandemic, the literature is nevertheless instructive about the effects of a dash for cash by large corporations in the early stages of the COVID pandemic or at the height of the 2007-09 financial crisis. For example, Greenwald, Krainer, and Paul (2020) find that banks that experienced larger drawdowns by large firms restricted term lending, crowding out credit of smaller firms. While drawdowns of credit lines increased total credit growth, their redistributive effects—to larger firms away from smaller ones—exacerbated the fall in investment. In this vein, Kapan and Minoiu (2021) find that, following the beginning of the pandemic, banks with larger portfolios of existing credit lines—and, hence, exposed to a higher risk of drawdowns—reported tightening lending standards on new C&I loans to both small and large firms, curtailed the supply of large syndicated loans, and reduced the number and volume of small business loans. They also find that the credit line drawdowns weighed on lending because of banks' lower risk tolerance rather than because of existing balance sheet (liquidity and capital) constraints. Their risk tolerance finding appears to be consistent with our narrative about concerns that banks have about drawn credit lines potentially becoming a drag on their capital. Kapan and Minoiu (2021)'s result is consistent with the findings of Ivashina and Scharfstein (2010) that banks more vulnerable to credit line drawdowns during the financial crisis cut back their lending to a greater extent. Our analysis suggests another dimension for the literature to explore: Not only exposures to credit lines matter for future lending decisions, but also the contract terms of these lines may play a role.

# References

Acharya, V. V., H. Almeida, and M. Campello (2013): "Aggregate Risk and the Choice between Cash and Lines of Credit," *Journal of Finance*, 68(5), 2059–2116.

Acharya, V. V., and N. Mora (2015): "A Crisis of Banks as Liquidity Providers," *Journal of Finance*, 70(1), 1–43.

Altavilla, C., M. Boucinha, J.-L. Peydro, and F. Smets (2019): "Banking Supervision, Monetary Policy and Risk-Taking: Big Data Evidence from 15 Credit Registers," Working paper, European Central Bank.

Aramonte, S., S. J. Lee, and V. Stebunovs (2019): "Risk taking and low longer-term interest rates: Evidence from the U.S. syndicated term loan market," *Journal of Banking and Finance*, forthcoming.

Barth, J. R., J. Caprio, Gerard, and R. Levine (2013): "Bank Regulation and Supervision in 180 Countries from 1999 to 2011," Working Paper 18733, National Bureau of Economic Research.

Berg, T., A. Saunders, and S. Steffen (2016): "The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees," *Journal of Finance*, 71(3), 1357–1392.

Berrospide, J. M., R. R. Meisenzahl, and B. D. Sullivan (2012): "Credit Line Use and Availability in the Financial Crisis: The Importance of Hedging," Discussion paper.

Carlson, M., and J. D. Rose (2017): "Stigma and the Discount Window," FEDS notes, Board of Governors of the Federal Reserve System.

Chang, X., Y. Chen, S. Dasgupta, and R. W. Masulis (2019): "External Financing of Last Resort? Bank Lines of Credit as a Source of Long-Term Finance," mimeo.

Cohen, G., M. Friedrichs, K. Gupta, W. Hayes, S. J. Lee, B. Marsh, N. Mislang, M. Shaton, and M. Sicilian (2018): "The U.S. Syndicated Loan Market: Matching Data," Working paper.

Correia, S. (2016): "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator," Working paper, Duke University.

Dell'Ariccia, G., L. Laeven, and G. A. Suarez (2017): "Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States," *Journal of Finance*, 72(2), 613–654.

Fischer, S. (2016): "The Lender of Last Resort Function in the United States," speech at a conference sponsored by the Committee on Capital Markets Regulation, Washington, D.C., Board of Governors of the Federal Reserve System.

Gatev, E., and P. E. Strahan (2006): "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market," *Journal of Finance*, 61(2), 867–892.

Greenwald, D. L., J. Krainer, and P. Paul (2020): "The Credit Line Channel," Working Paper Series 2020-26, Federal Reserve Bank of San Francisco.

Ioannidou, V., S. Ongena, and J. Peydro (2015): "Monetary Policy, Risk-Taking and Pricing: Evidence from a Quasi-Natural Experiment," *Review of Finance*, 19(1), 95–144.

Ivashina, V., and D. Scharfstein (2010): "Bank lending during the financial crisis of 2008," *Journal of Financial Economics*, 97(3), 319–338.

Jimenez, G., S. Ongena, J. Peydro, and J. Saurina (2014): "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say about the Effects of Monetary Policy on Credit-Risk Taking?," *Econometrica*, 82(2), 463–505.

Kapan, T., and C. Minoiu (2021): " Liquidity Insurance vs. Credit Provision: Evidence from the COVID-19 Crisis," Discussion paper.

Kashyap, A. K., and J. C. Stein (2000): "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?," *American Economic Review*, 90(3), 407–428.

Khwaja, A. I., and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98(4), 1413–42.

Lee, S. J., L. Q. Liu, and V. Stebunovs (2019): "Risk-taking spillovers of U.S. monetary policy in the global market for U.S. dollar corporate loans," *Journal of Banking and Finance*, forthcoming.

——— (2020): "Risk-mitigating Effects of Being Prompt and Transparent," *mimeo*.

Merton, R. C. (1974): "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*, 29(2), 449–470.

Nazeran, P., and D. Dwyer (2015): "Credit Risk Modeling of Public Firms: EDF9," Discussion paper, Moody's Analytics.

Plosser, M., and J. A. C. Santos (2018a): "The cost of bank regulatory capital," Staff Reports 853, Federal Reserve Bank of New York.

Plosser, M. C., and J. A. C. Santos (2018b): "Banks Incentives and Inconsistent Risk Models," *Review of Financial Studies*, 31(6), 2080–2112.

Roberts, D., A. Sarkar, and O. Shachar (2018): "Bank Liquidity Creation, Systemic Risk, and Basel Liquidity Regulations," Staff Reports 852, Federal Reserve Bank of New York.

Roberts, M. R., and A. Sufi (2009): "Renegotiation of financial contracts: Evidence from private credit agreements," *Journal of Financial Economics*, 93(2), 159–184.

Wu, J. C., and F. D. Xia (2016): "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 48(2-3), 253–291.

Yankov, V. (2020): "The Liquidity Coverage Ratio and Coporate Liquidity Management," FEDS notes, Board of Governors of the Federal Reserve System (U.S.).