BIS Working Papers
No 1323

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Monetary and Economic Department

January 2026

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Banks and capital requirements: evidence from countercyclical buffers*

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January 15, 2026

ABSTRACT

When capital requirements rise, banks can raise equity or reduce risk-weighted assets, typically by cutting lending. We show they also use credit default swaps (CDS). Linking EU trade-repository CDS data to syndicated loans for November 2017 to April 2024, we document that banks significantly increase CDS hedging on loans to firms in countries that raise their countercyclical capital buffer (CCyB). Our identification exploits within-bank comparisons of hedging for similar borrowers across countries with different CCyB rates. A 1 percentage point increase in the CCyB reduces the uninsured share of a loan by about 53 percentage points, with the strongest effects for banks most exposed to the buffer-raising country. Eligible credit risk transfer via CDS thus emerges as a first-order channel through which banks accommodate tighter capital requirements, potentially attenuating macroprudential policy transmission.

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*This paper supersedes findings from a previous one titled "Syndicated loans and CDS positioning". We thank Max Bruche, Stijn Claessens, Pierre Collin-Dufresne, Stine Louise Daetz, Marco D'Errico, Ingo Fender, Jon Frost, Blaise Gadanecz, Leonardo Gambacorta, Jan Pieter Krahnen, Tuomas Peltonen, Wolf Wagner, Mark Wahrenburg, Adam Zawadowski, Xin Zhang and seminar/conference participants at the RiskLab/ESRB/Bank of Finland SRA conference, BIS, ESRB/ECB, Goethe University, Frontiers of Finance, EEA, Swiss Winter Conference on Financial Intermediation, and the 3rd IWH-FIN-FIRE workshop on Challenges to Financial Stability for helpful comments and suggestions.

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Declaration of interest: none. The views expressed here are those of the authors and do not necessarily reflect those of the Bank for International Settlements or the European Central Bank. All errors are the authors' responsibility. The dataset used in this paper contains confidential statistical information. The analysis in the paper ensures that no confidential information is shown. Data use has been approved by the relevant ECB decision-making bodies.

1 Introduction

Higher capital requirements give banks two main adjustment margins: raise equity or reduce risk-weighted assets. While Modigliani and Miller (1958) suggest equity issuance should be neutral, the empirical literature finds that banks predominantly cut lending when constraints tighten (Gropp et al., 2019; Fraisse et al., 2020). Identifying the response of banks to capital requirements is difficult: truly exogenous shifts in requirements are rare,[1] and visibility into alternative adjustment margins was limited until recently (such as transferring credit risk through market instruments like credit default swaps (CDS)).

We document that banks also respond to higher capital requirements by making use of CDS to reduce risk-weighted assets. We leverage changes to the countercyclical capital buffer (CCyB), which provides policy-driven country-time variation to study how banks manage capital charges beyond lending decisions. Using loan-level syndicated lending data and granular transaction-level data on the single-name CDS market, we construct a borrower-specific uninsured loan ratio for each bank at monthly frequency and exploit cross-country variation in CCyB rates in a panel with firm×time and bank×time fixed effects, controlling for banks' index-CDS activity. When CCyB rates rise in a borrower's country, banks significantly increase CDS hedging on those loans: a 1 percentage point increase in the CCyB reduces the uninsured loan ratio by about 53 percentage points at implementation, with smaller adjustments at announcement. The response is strongest for banks with larger pre-existing exposures to the buffer-raising country and is robust across samples and controls. These findings indicate that eligible credit risk transfer via CDS is a first-order channel through which banks accommodate tighter capital requirements, potentially attenuating macroprudential policy transmission.

Our analysis links transaction-level single-name CDS positions from EU trade-repository reports to syndicated loan exposures at the bank–firm–month level and augments these

[1]Existing studies have focused on bank lending using loan level data from regulatory authorities (Fraisse et al., 2020) or exploited the European Banking Authority's (EBA) capital exercise as an exogenous shock to capital requirements (Gropp et al., 2019).

with bank balance-sheet controls. We leverage a regulatory dataset on banks' CDS trading from the European Market Infrastructure Regulation (EMIR) which identifies banks' hedging positions at the firm level.[2] We merge the CDS position of bank i towards firm j (i.e. buying or selling of protection in the single-name CDS market) with the amount of syndicated lending that bank i provided to firm j to calculate the share of the loan that has not been insured using derivatives. We refer to this as the "uninsured loan ratio",[3] a directly interpretable measure of hedging intensity that we build at monthly frequency for November 2017 to April 2024.[4]

As exogenous variation in capital requirements, we employ changes in the CCyB in the countries where the firms that banks lend to are located. We find that banks hedge more of their loans to firms in countries that increase their CCyB rates, indicating that banks use credit derivatives to reduce their risk-weighted asset position. This effect holds even when comparing loan and hedging positions by the same bank in a given month toward (otherwise identical) firms domiciled in different countries, where one country raises its CCyB rate while the other does not.

We begin by documenting some stylized facts about hedging through the lens of the uninsured loan ratio. Controlling for time-invariant bank characteristics, and again only considering firms for which there is a CDS available during our sample ("CDS traded firms"), we show that banks that are active in the index CDS market tend to hedge less of their loans using a single-name CDS contract, suggesting that banks engage in so-called proxy hedging.[5] Controlling for bank-level index market activity is therefore important when trying to assess hedging in response to bank regulation. Banks also tend to hedge more the higher the

[2]Following the commitment by G20 leaders in the 2009 Pittsburgh summit to make the OTC derivatives market more transparent, the European Union (EU) enacted EMIR, which requires that all European counterparties engaging in derivatives transactions to report these trades.

[3]In particular, for all bank-firm pairs in any given period, we compute the ratio of the loan exposure minus the net protection bought (gross protection bought minus gross protection sold) over the loan exposure.

[4]Our sample includes 388 banks from 21 countries lending to 1015 firms from 46 countries.

[5]For any given bank and month, we define the indicator of index market activity as the ratio of net (protection buying minus selling) to gross (buying plus selling) positions in the index market, times the logarithm of gross positions.

riskiness of the firm (as captured by CDS spreads), although the effect lacks statistical power (partly due to the reduction in sample size implied by matching with CDS spreads data). To overcome this issue we exploit the granularity of our data and control throughout for $firm \times time$ fixed effects, which absorb all time variation specific to a given firm, including – but not limited to – their riskiness. We also find that more leveraged banks tend to insure less, as do banks with higher liquidity as measured by the ratio of liquid assets to deposits and short-term funding. Finally, the evidence points to better capitalized, more profitable and bigger banks insuring more, although the estimates are not statistically significant.

In our main results, we use changes in the CCyB in countries where the firms that banks lend to are located to assess how banks' hedging behavior is affected. We begin by considering the entire sample of CDS traded firms. Controlling for time-varying firm characteristics, as well as banks' index market activity and a measure of the concentration of lending of banks, *ctryconc* which is a measure of lending concentration in the country of firm j by bank i, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i, we find that banks hedge a greater portion of loans issued to firms domiciled in countries with higher CCyB rates. Even when adding controls for time-varying bank characteristics through $bank \times time$ fixed effects, the coefficient on the CCyB remains highly statistically significant.

Our estimates are not only statistically but also economically significant. A one percentage point (pp) increase in the CCyB rate leads to a 50-54 pp decrease in the uninsured loan ratio (equivalently, increases the insured share). This implies that banks more than double their hedging activity for loans affected by the buffer, insulating a majority of the loan value from the higher capital charges. This demonstrates that the use of CDS for regulatory capital relief is a first-order strategic response for banks facing tighter capital requirements.[6] The CCyB successfully forces banks to hold more capital against their loans, but they can

[6] A fully hedged loan (where the credit risk is transferred) could qualify for a much lower risk weight, potentially as low as 0% if the protection seller is a bank with a 0% risk weight and the hedge is perfectly matched.

also achieve this through hedging rather than just cutting lending.[7]

Even though our granular $firm \times time$ and $bank \times time$ fixed effects absorb a substantial amount of variation, results could be driven by other factors. Most notably, some banks that lend to non-financial corporations in the syndicated loan market are not active in the CDS market at all, either out of choice or because they do not have access (due to e.g. high costs of entry). We find that when further restricting the sample to consider only banks that are active some time during our sample period ("CDS active banks"),[8] our main results go through largely unchanged. Similarly, when considering a sample that excludes all observations in which the uninsured loan ratio equals one (i.e. when there is (on net) neither hedging nor doubling down of exposures), results remain statistically and economically significant.

While our main analysis focuses on the point in time when CCyB rates become effective, banks could potentially reduce risk-weighted assets by purchasing CDS as soon as CCyB rate changes are announced.[9] To examine this, we repeat our analysis to investigate hedging behavior following the announcement of CCyB rate changes. The results are very similar to our main findings, albeit with a much smaller magnitude.

Finally, we document significant heterogeneity in banks' responses. The propensity to hedge using CDS following a CCyB increase is significantly stronger for banks that have larger pre-existing loan exposures to the country implementing the buffer. This indicates that the adjustment through derivatives is a strategic response most employed by banks for whom the new capital requirement would be most binding, highlighting the economic materiality of the mechanism we identify.

Our findings have significant implications for both financial regulation and research. For policymakers, the results highlight a critical, albeit complex, trade-off. While a liquid

[7]To be sure, banks may still cut lending, especially to smaller firms which are not captured in our analysis (i.e., firms with no CDS written on them.

[8]With this sample, we have 61 banks from 17 countries lending to 995 firms from 46 different countries.

[9]Since buying CDS is costly for banks, they would likely do so only in a liquid market after the implementation of CCyB rate changes, when the loan position becomes more expensive.

CDS market can dampen the potential negative impact of macroprudential tools on credit supply by providing banks with an alternative adjustment mechanism, it simultaneously introduces a channel for arbitrage. This suggests that the effectiveness of countercyclical capital buffers in constraining bank risk-taking may be partially attenuated, potentially shifting risk into the less transparent derivatives market and raising new financial stability concerns. For academic research, this paper moves beyond the established narrative of balance sheet adjustment through lending cuts and asset sales. We provide robust evidence of a market-based response to regulation, thereby integrating the literature on bank capital requirements with that on derivatives usage and credit supply. This opens new avenues for studying the interconnectedness of modern banking, market liquidity, and the transmission of macroprudential policy.

Related literature and contribution. Our analysis contributes to the literature in two important ways. First, we document the use of credit derivatives as a novel channel through which banks respond to increasing capital requirements. Several studies have documented various ways in which banks adjust their balance sheets in response to capital requirements (Berrospide and Edge, 2010; Gambacorta and Shin, 2018). Gropp et al. (2019) and De Roure et al. (2022) show that low-capitalized banks reduce risk-weighted assets by curtailing lending.[10] Blattner et al. (2023) find that banks facing capital shortfalls during the 2011 EBA Special Capital Enhancement Exercise cut lending and reallocate credit toward distressed firms with under-reported loan losses. Moreover, Irani et al. (2021) document that undercapitalized banks shift syndicated loans to the shadow banking sector through secondary market sales.[11] De Jonghe et al. (2020) highlight that Pillar 2 capital requirements lead to a contraction in credit supply, particularly affecting large, risky, and low-cost borrowers, while Imbierowicz et al. (2018) find that Basel II implementation in Denmark resulted in increased

[10]De Roure et al. (2022) notes that this is partly offset by an increase in peer-to-peer (P2P) lending.

[11]While this literature has primarily focused on adjustments to the loan portfolio itself, a parallel strand of research has considered the role of credit derivatives in facilitating credit supply. A seminal contribution is Hirtle (2009), who finds limited evidence that banks' use of CDS is associated with greater credit availability.

bank capital ratios but also reduced asset risk. While these studies have primarily focused on how banks reduce their asset positions by cutting lending or selling loans, we provide evidence that banks also use derivatives for capital relief, i.e. to manage their capital constraints. Our findings complement the work of Saretto and Tookes (2013), who show that the existence of a liquid CDS market allows firms to obtain longer-maturity loans, likely because banks can hedge the associated risk. We identify the specific regulatory capital motive – the activation of countercyclical buffers – that could drive this hedging behavior.

Second, our paper contributes to the literature on macroprudential policy instruments. For example, Acharya et al. (2022) examine loan-to-income and loan-to-value limits as regulatory constraints on households and find that banks reallocate mortgage loans from low- to high-income borrowers, while simultaneously increasing risk in their securities holdings and corporate credit portfolios. Furthermore, Akinci and Olmstead-Rumsey (2018) provide cross-country evidence on the impact of macroprudential policies on credit growth and financial stability, highlighting their role in reducing systemic risk (see also Cerutti et al. (2017) for a broad overview on the use and effectiveness of macroprudential policies). In particular, with the focus on CCyB, our paper enhances the understanding of how banks respond to countercyclical capital buffers. Prior research has primarily documented CCyB effects on lending behavior, showing that banks reduce credit supply when capital requirements tighten (Buch et al., 2021), with spillovers to lending to other sectors (Auer et al., 2022).[12] Additionally, Jiménez et al. (2017) analyze the effectiveness of dynamic provisioning and CCyB policies in Spain, demonstrating that these macroprudential tools can help mitigate credit supply contractions during economic downturns. However, less is known about how banks adjust their risk exposure through derivatives in response to CCyB changes. Our findings suggest that banks actively use CDS to manage capital constraints, adding a new dimension to the discussion on the effectiveness and unintended consequences of countercyclical capital buffers.

[12]Beyond the CCyB, Cizel et al. (2019) document substitution to nonbank credit.

Roadmap. The remainder of the paper is organized as follows. In Section 2, we introduce the datasets used and how we bring them together, discuss the main variables used in the empirical analysis, and present descriptive statistics. Results, including robustness exercises, are shown in Section 3. Section 4 concludes.

2 Data and measurement

2.1 Data

We use granular data from various sources and match them by a combination of bank and company identifiers. The three main datasets we use are: Thomson Reuters DealScan for syndicated loan data, the transaction-level CDS derivatives positions obtained under the reporting obligation of the EMIR regulation in Europe,[13] and bank-level balance sheet data from ORBIS. Figure 1 summarizes the datasets and how they fit together in the context of our project. We go over each dataset in detail below.

Lending data. We obtain loan-level data from Thomson Reuters DealScan, which provides information on the terms and conditions of deals in the global syndicated loan market. In this market, two or more banks (the "syndicate") agree to grant loans to companies, under the leadership of one of the banks (the "lead arranger", who is responsible for most of the pre- and post-loan duties associated with bank lending). Lending is organized in packages and facilities: a package is a loan agreement between a borrower and a group of lenders, and each package can contain one or more facilities. Our basic unit of observation is the facility. We identify the identity and location of both borrower and lenders, as well as a rich set of loan characteristics. We focus on borrowers that are non-financial corporations, as well as

[13]The European Market Infrastructure Regulation (EMIR), which became effective in 2014, requires that all EU counterparties engaging in derivatives transactions report them to trade repositories authorized by the European Securities Markets Authority (ESMA). The trade repositories are then obliged to report to the relevant national authorities. For details on the regulation see the dedicated website of the European Commission. For a first look at the data see Abad et al. (2016).

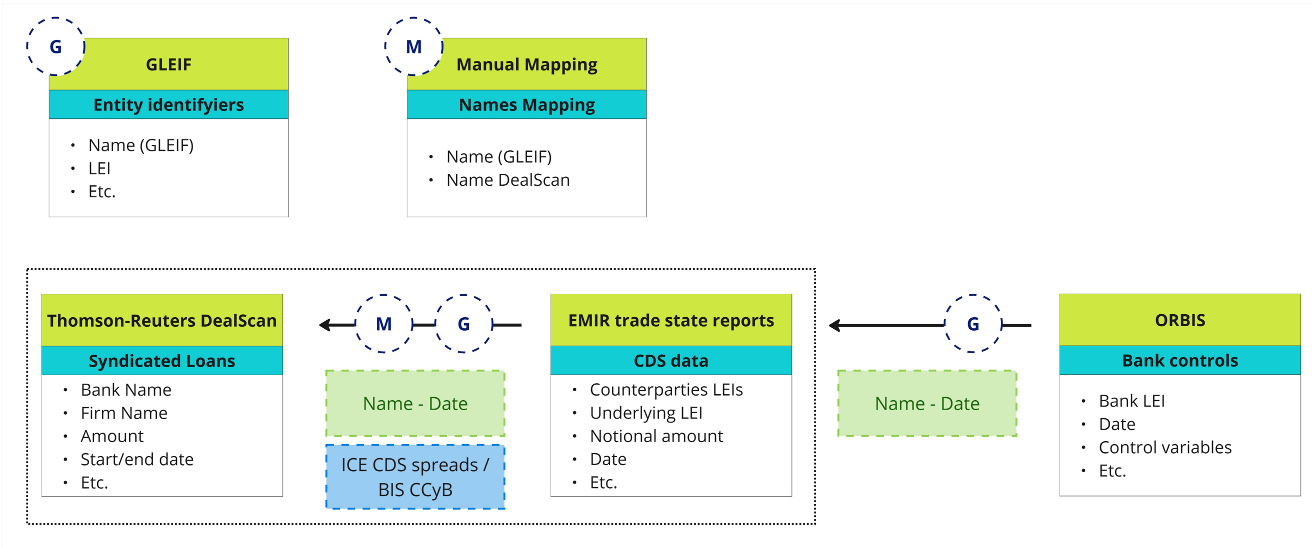

Figure 1: Overview of datasets and merging

on loan agreements with facility end date after November 2017. We convert all non-euro loan amounts into euro at the exchange rate prevailing at loan origination.

Derivatives data. We obtain transaction-level derivatives data from the European Central Bank (ECB). The data are sourced from the registered trade repositories under the EMIR regulation.[14] In particular, we use end-of-month "Trade State Reports" (TSR) ranging from November 2017 to April 2024.[15] Trade State Reports present the stock of all transactions as of a given date, thereby providing a snapshot of the entire market.

We perform an extensive cleaning procedure to take the data from its raw form to a state in which it can be used for analysis (see Abad et al. (2016) for details).[16] One feature of the data, as related to the regulation that underpins it, is worth noting: the regulation requires that *all* EU counterparties engaging in a derivative transaction report it to an authorized

[14] The full list of trade repositories is available here.

[15] There are Trade State Reports under the EMIR framework since April 2014, but due to poor data quality we leave them out of the analysis. Following the "Big Bang" and "Small Bang" (see Markit (2009)), the market has become very standardized along many dimensions, most notably maturity. The CDS market is particularly standardized at the five-year mark. Therefore, with snapshots from 2017, we are able to get a fair glimpse of the market five years back.

[16] The cleaning procedure involves getting rid of outliers, dropping duplicates, eliminating inconsistent/erroneous observations, dropping intragroup transactions, etc.

trade repository. We are thus sure to see the entire market for EU counterparties, but we cannot say the same about non-EU counterparties. We only see the latter to the extent that they are *reported* (as opposed to *reporting*). The focus of our analysis is therefore on EU-based banks, as in this case we are certain that, were there to be CDS activity, we should see it in the data.[17]

In their raw form, the data present information on a trade-by-trade basis, with dozens of variables for each trade. The main variables of interest are, besides the identity of reporting and reported counterparties: the identity of the underlying reference entity, the notional amount,[18] and the effective and maturity dates. To identify counterparties, we use Legal Entity Identifiers (LEIs), complemented with the GLEIF dataset. We use this library to identify the sector of all counterparties, using information from EMIR, which allows for this mapping between LEIs and sectors.[19] Importantly, since our focus is on non-financial corporations (NFCs), we exclude all trades on an ISIN not associated with an NFC.

We focus on the single-name portion of the CDS market, as in most studies. Because of how data are reported under EMIR, CDS contracts written on indices or bespoke baskets are since the fourth quarter of 2015 only identified with an "I" or a "B". This does not allow for a decomposition of the index into single-name equivalents. Nonetheless, we use the index market data to construct a bank-specific measure of index market activity that we include as control in our main regressions. We build a summary measure of the overall activity of banks in the index market (IMA_{it}) as the net-to-gross ratio multiplied by the logarithm of total (index) market activity. In particular, if we define gross buying and selling of protection by bank i in the index market in period t as b_{it}^I and s_{it}^I respectively, then $IMA_{it} = \frac{b_{it}^I - s_{it}^I}{b_{it}^I + s_{it}^I} log\left(b_{it}^I + s_{it}^I\right)$.[20] We merge this indicator with our main dataset based

[17]Accordingly, throughout our analysis we exclude banks from the United Kingdom from the sample. Our results are however robust to their inclusion.

[18]We also convert all non-euro notional amounts to euro using the appropriate exchange rates.

[19]Using the ISIN information to identify the underlying reference entities, we also use ICE CDS spreads to retrieve CDS spreads.

[20]Taking the net-to-gross ratio alone would not distinguish between dealers, who have small net to gross positions but are generally very active in the market, and other intermediaries who might have both small net to gross positions and limited market activity.

on LEIs.

Beyond the focus on NFCs and the single-name market, we only consider transactions in which at least one counterparty is a financial institution. In order to combine the EMIR data with syndicated loan data, we use LEI information (whenever available) or otherwise hand-matched the counterparties of CDS transactions with lender names in Dealscan as well as the ISIN identifiers of the reference underlying (EMIR) and borrower (Dealscan).

Bank balance sheet data. We retrieve bank balance sheet information from ORBIS. We match these data with syndicated loan data using LEIs. We retrieve information on size (total assets), performance (return on average assets), liquidity (liquid assets over deposits and short term funding) and risk (leverage and the Tier 1 capital ratio (TIER1 ratio)). We use these data as controls in some regressions.

Additional data. Finally, we complement the data above with information on CCyB announcements and implementations at the country level from the BIS and the ESRB, as well as data on global legal entity identifiers (GLEIF). Figure 2 summarizes announcements and implementation of CCyB changes as an average over time and countries, whereas Figure 3 presents the detail by country, again split by effective and announced. We use implementation in our baseline results, and present robustness exercises in terms of announcements. Announced CCyB tend to be higher than actually implemented CCyB, as many announcements were not actually implemented (most notably in the run-up to the Covid-19 pandemic). After the pandemic, announcements started picking up around the second half of 2021, with actual implementation following in line with implementation lags.

Construction of the sample. We start the construction of our sample by taking all syndicated loans that mature after November 2017 and calculate for each bank-firm relation the end of month stock of outstanding loans for the period between November 2017 and April 2024. From the EMIR CDS data, we likewise calculate for each bank-reference underlying

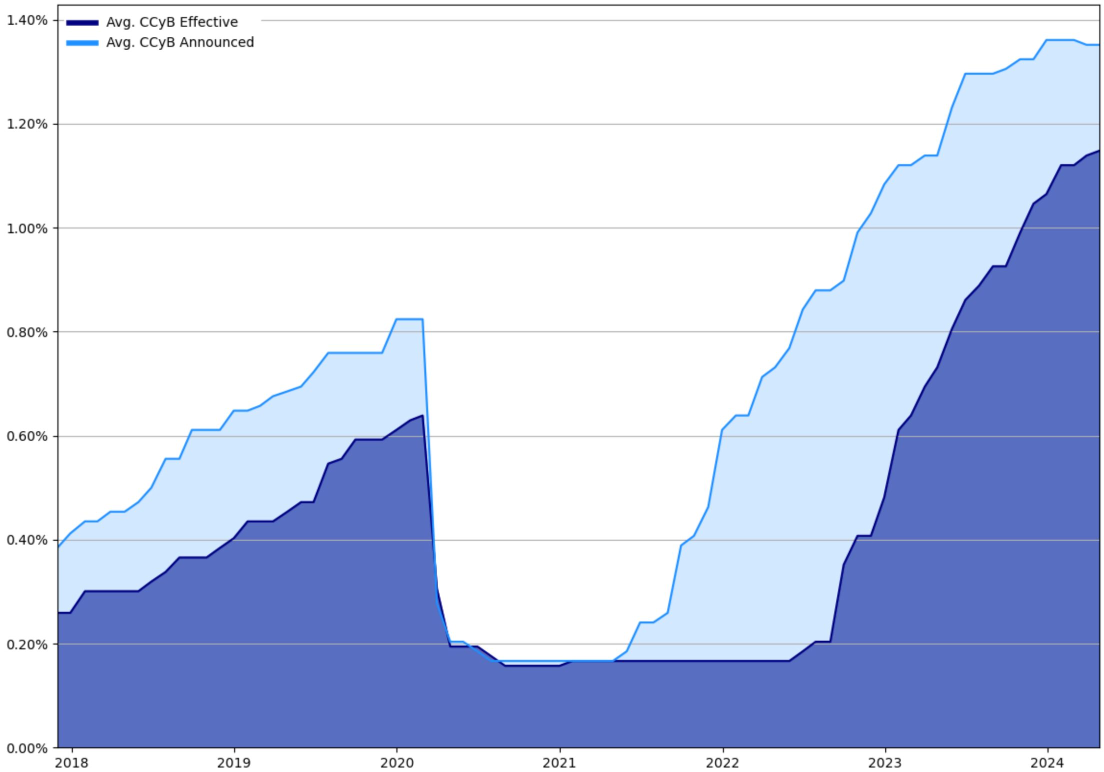

Figure 2: Average CCyB values over time (announcements and effective)

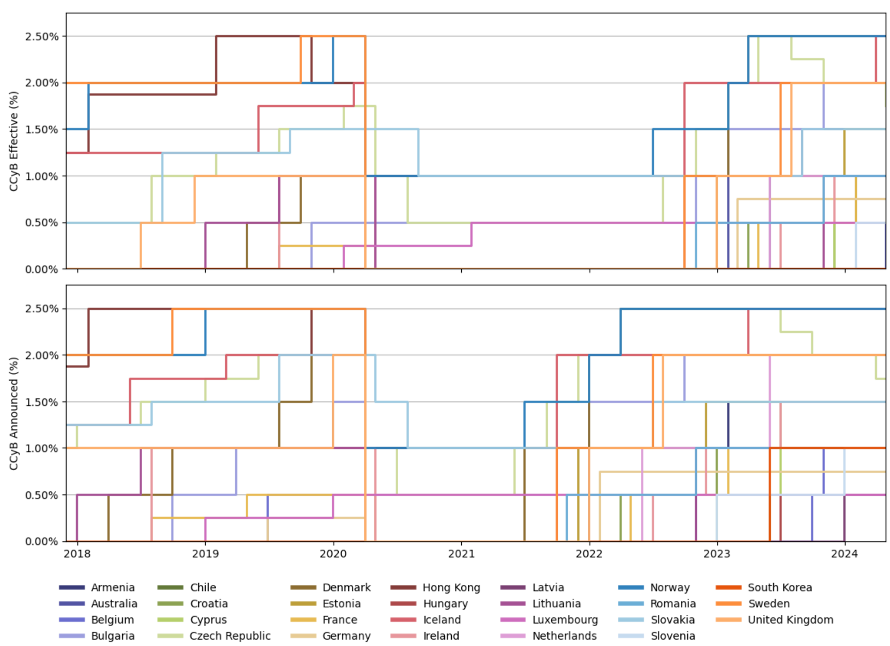

Figure 3: Effective and announced CCyB values over time

(firm) relation the aggregate end-of-month stock of notional amount of CDS outstanding both for the bank as a protection seller as well as for the bank as a protection buyer in a given month between November 2017 and April 2024. This allows us to observe the stock of net protection for bank i with respect to firm j in month t. We then merge the CDS information to the loan data on the bank i – firm j – time t level so that we observe, for each outstanding loan volume on the bank-firm level, the corresponding net notional stock of CDS bank i holds on firm j as the reference underlying of the CDS at time t. We drop all CDS information that did not match with the loan data, so our sample comprises all outstanding syndicated loans between November 2017 and April 2024. We merge banks' balance sheet information to the data, as well as market CDS quotes from ICE CDS spreads for the firms that have a CDS written on them. We exclude observations for UK banks throughout our analysis.

The ability to hedge (or double down) exposures to a given firm may be constrained by two main factors – the first coming from the firm's side, the second from the bank. A bank lending to a firm may want to hedge (or double down) the exposure, but there just may be no market for CDS on that firm. Accordingly, throughout our analysis we restrict the sample to consider only *CDS traded firms*: those firms for which there is a CDS available between November 2017 and April 2024.[21]

In addition, many of the banks that provide loans in a syndicate are in fact not active in the CDS market at all. This can be either out of choice, or because they do not have access to it due to, say, high fixed costs of entry. In some specifications we additionally restrict the sample to banks that are *CDS active*. We define CDS active banks as those that had at least one active CDS trade in the period between November 2017 and April 2024, and thus appeared at least once in the EMIR database.[22] By combining the sets of CDS active banks and CDS traded firms we can be confident that the lack of CDS activity is not due to either

[21]The index of market activity discussed before also helps us to control for the proxy hedging that may arise when there are no direct hedging options available.

[22]In this way, we assuage concerns that any lack of hedging we observe is simply due to lack of access to the market instead of a deliberate decision not to hedge a specific credit exposure.

the bank not having access to the market or the firm not having a CDS written on it.[23]

2.2 Measurement: uninsured loan ratio

To explore the effect of CCyB changes on banks' hedging behavior, we construct a measure of the share of loans that remains uninsured. This measure, which we label the uninsured loan ratio (henceforth ULR_{ijt}), varies at the bank i – firm j – time t level. We first derive the net notional amount of CDS protection on reference entity j by bank i at time t as the difference between the sum of bank i's CDS protection bought on reference entity j from any protection seller k and the aggregate amount of bank i's CDS protection sold on reference entity j to any protection buyer k,

$$\begin{aligned} &net\ notional\ CDS\ holding_{ijt} \\ &\quad = \sum_k net\ notional\ CDS\ buying_{ijt,k} - \sum_k net\ notional\ CDS\ selling_{ijt,k} \end{aligned} \tag{1}$$

Next, we compute the difference between the stock of loans from bank i to firm j in the loan portfolio of bank i at time t and the net notional holdings of CDS protection of bank i on reference entity j at time t as a ratio to the loan amount of bank i to firm j at time t:[24]

$$ULR_{ijt} = \frac{loan\ holding_{ijt} - net\ notional\ CDS\ holding_{ijt}}{loan\ holding_{ijt}}. \tag{2}$$

We winsorize ULR_{ijt} at the 0.05%/99.95% level to eliminate the influence of extreme outliers. When bank i does not buy or sell (on net) protection on firm j at time t, then

[23] Our results are robust to alternative sample specifications that either include non CDS-traded firms, CDS-inactive banks, or both.

[24] In order to assign facility amounts to the different banks participating in the syndicates, we use the lender share variable whenever available, which gives an exact break-up of the contribution of each bank to the facility. When these shares are not available, we construct average shares by "lender role type", distinguishing between the different top-tiers of arrangers versus plain "Participants" (for a similar approach, see Bräuning and Ivashina, 2017), and use these average shares to distribute the lending in the syndicates for which we do not observe the lender shares.

$ULR_{ijt} = 1$. When $ULR_{ijt} > 1 (< 1)$, bank i is doubling-up (hedging, at least partly) its credit risk exposure to firm j. ULR_{ijt} can in fact take negative values if bank i over-insures (i.e. buys net protection on firm j over and above its loan exposure). Figure 4 presents the relative frequency of the uninsured loan ratio for the sample of CDS traded firms and CDS trading banks.[25] The ULR is centered around 1 and has similar mass on either side. In some regression specifications we will exclude observations for which the ULR equals one.

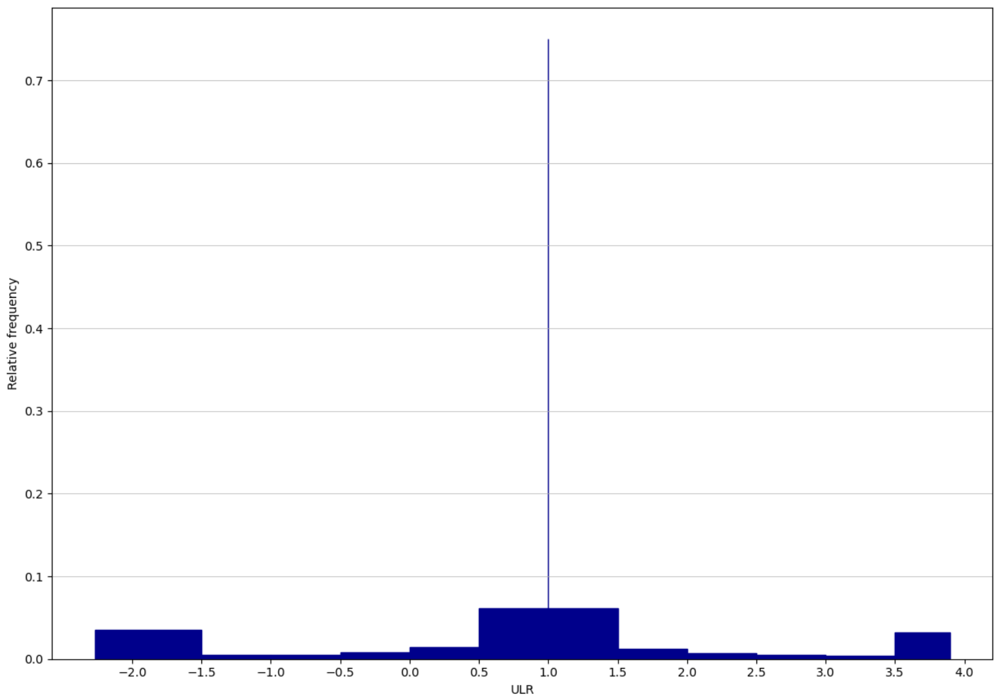

Figure 4: Relative frequency of the uninsured loan ratio (ULR)

2.3 Descriptive statistics

Our sample features a large coverage of both banks and firms. When considering CDS traded firms, our sample includes 388 banks from 21 countries, lending to 1015 firms from 46 different countries. When restricting the sample to also have CDS active banks, we have 61 banks from 17 countries, lending to 995 firms from 46 different countries.[26] Despite restricting

[25] For confidentiality reasons, we present this in buckets for relative frequencies.

[26] Were we not to constrain the sample by CDS traded firms and CDS active banks, we would have 1928 banks from 28 countries lending to 24544 firms located in 146 countries.

the sample substantially, even when considering CDS traded firms and CDS active banks the number of lenders and borrowers is significantly larger than in the previous literature studying the CDS market.

Table 1 provides descriptive statistics, split between the sample that considers CDS traded firms (Panel A) and that when we further restrict to CDS active banks (Panel B).

On average, the uninsured loan ratio is around 98%, i. e., on average, banks use CDS as protection against credit events rather than as a speculative instrument to double down their credit risks. A non-negligible number of banks neither insures nor doubles down risks (i.e. they have ULR = 1). We observe a high maximum for the ULR, as well as a negative minimum (i.e. over-insurance, at least with respect to syndicated loan exposures).

Bank characteristics are broadly similar in the two samples we consider. The average balance sheet size (in logs) stands around 27. Capitalization as measured by the Tier 1 ratio tends to be high at around 15%, with lower standard deviation for those banks that are active in the CDS market. Leverage, defined as the ratio of Tier 1 capital to total bank assets, stands at around 4.5%, without much different across subsamples. Measures of liquidity (liquid assets over deposits and short-term funding) and profitability (return on average assets) are also similar across samples. The share of liquid assets stands between 78 and 80%, whereas profitability is positive but, as is well known, quite low.

Table 1: Summary statistics

Panel A: CDS traded firms					
	Obs	Mean	Std. Dev.	Min	Max
ULR	378 212	0.981	0.487	−0.974	2.596
Size	294 074	27.324	0.962	NA	NA
Tier1	291 477	15.539	4.224	NA	NA
LEV	291 894	0.045	0.020	NA	NA
LIQ	294 008	77.868	52.767	NA	NA
ROA	293 786	0.332	0.404	NA	NA
IMA	378 212	1.328	5.163	−21.143	21.044
Panel B: CDS traded firms and CDS active banks					
	Obs	Mean	Std. Dev.	Min	Max
ULR	286 056	0.976	0.861	−2.268	3.893
Size	281 649	27.403	0.855	NA	NA
Tier1	279 631	15.490	2.511	NA	NA
LEV	279 949	0.044	0.016	NA	NA
LIQ	281 620	79.631	49.374	NA	NA
ROA	281 649	0.325	0.321	NA	NA
IMA	286 056	1.532	5.552	−21.143	21.044

Notes: ULR is the uninsured loan ratio defined in (2). $Size$ stands for the logarithm of total assets, $Tier1$ for core equity capital to total risk-weighted-assets, LEV for leverage, defined as Tier 1 capital over total assets, LIQ for liquid assets over deposits and short-term funding, ROA for the return on average assets, and IMA stands for the index market activity indicator. For confidentiality reasons we cannot show minimum and maximum values for bank-specific metrics. In regression analyses all variables are lagged by one period except for IMA.

3 Results

Hedging behavior and bank and firm characteristics. We begin by providing descriptive evidence of how the uninsured loan ratio correlates with bank and firm characteristics. In particular, we model the uninsured loan ratio relating bank i to firm j at time t as a function of bank and firm characteristics (firm risk). At the same time, we control for bank-specific (e.g. management style, corporate culture) and borrower-specific (e.g. industry) characteristics, as well as time fixed effects which absorb all variation that is time-specific and common to all banks (e.g. changes in regulation, global risk aversion, etc.). In a stronger specification we absorb firm-specific time-varying confounding factors by including $firm \times time$ fixed effects. Since this includes, but is not limited to, firm riskiness, in such specifications we cannot include a proxy for firm risk (i.e. firm CDS spreads).

The baseline specification is thus given by:

$$ULR_{ijt} = \alpha_i + \alpha_t + \alpha_j(+\alpha_{jt}) + \kappa \cdot CDS_{j,t-1} + \boldsymbol{\beta'} \cdot \boldsymbol{BC}_{it-1} + \epsilon_{ijt} \tag{3}$$

where CDS_{jt} captures the firm riskiness and is represented by the market CDS spread of firm j in period t, and $\boldsymbol{BC}_{it} = (LEV_{it}, LIQ_{it}, ROA_{it}, TIER1_{it}, SIZE_{it}, IMA_{it+1})'$ is a vector containing different bank-specific characteristics such as different types of risk measures (LEV_{it} = leverage and LIQ_{it} = liquid assets over deposits and short-term funding), profitability (ROA_{it} = return on average assets), capitalization (the regulatory TIER1 capital ratio), size (log of total assets),[27] and the proxy measure for index market activity (IMA_{it}) to control for portfolio hedging and general market positioning.[28] We lag the bank-specific variables by one period to avoid endogeneity. The only exception is IMA_{it}, which is used contemporaneously in order to capture contemporaneous substitution effects between single name and index CDS hedging. $Bank$, $time$, $firm$ and $firm \times time$ fixed effects are captured

[27] Evidence suggest the existence of a positive link between size and hedging (e.g. Purnanandam (2007), Ellul and Yerramilli (2013)). Controlling for size is important as it ensures that the effects we are after are not driven by a reduction in lending or assets. We control for size ($SIZE_{it}$) throughout all our regressions.

[28] As discussed above, this index is defined as the product between the net-to-gross ratio in the index market and the logarithm of total index market activity. Taking the net-to-gross ratio alone would not distinguish between dealers, who have small net to gross positions but are generally very active in the market, and other intermediaries who might have both small net to gross positions and reduced market activity. This index also serves as a way to control for the nature of different players (say, banks that are more intensely involved in dealing).

by α_i, α_t, α_j and α_{jt}, respectively.

The corresponding parameters are collected in the vector $\boldsymbol{\beta'} = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$. We expect $\kappa < 0$, that is, higher firm risk as captured by firms' market CDS spreads should be associated with a smaller share of the loan being uninsured. More importantly, regarding bank-specific indicators, we expect the coefficients to be positive when looking at bank risk measures ($\beta_1, \beta_2 > 0$) and negative when considering profitability $\beta_3 < 0$.

Results are presented in Table 2.[29] We include bank fixed effects in all specifications in order to control for time-invariant bank characteristics. The coefficient estimate on the index of market activity is positive and highly statistically significant, implying that banks that engage in the index CDS market insure a smaller share of their syndicated credit exposures using single-name CDS contracts. Controlling for proxy hedging through index market activity is therefore important. The estimates in columns (2) and (3) suggest that when the riskiness of firms increases banks tend to insure more (i.e. the uninsured loan ratio declines), although the estimate is not statistically significant.[30] In columns (4)-(9) we absorb all firm characteristics that vary over time (including, but not limited to, their riskiness) and sequentially include bank-specific controls. More leveraged banks insure less, as do banks with higher liquidity. Better capitalized, more profitable and bigger banks tend to insure more, although the point estimates are not statistically significant.

Banks' response to countercyclical buffers. Next, we move to our main results on how banks react to capital regulation through the lens of the countercyclical buffer. We expand on the baseline specification in equation 3 by including a measure of the effective CCyB in the country of firm j ($CCyB_{j^c t}$).[31]. Concretely, our regression specification is as follows:

[29] The table presents results excluding observations where $ULR_{ijt} = 1$. Results are robust to including these observations, which roughly quintuple the size of the sample.

[30] Sample size is reduced substantially, as we are only able to retrieve market CDS information for a subset of firms.

[31] We use the superscript c to indicate the country of borrower j

$$ULR_{ijt} = \alpha_i + \alpha_{jt} + \alpha_{it} + \beta \cdot CCyB_{jt} + \gamma_1 \cdot ctryconc_{ij^ct} + \gamma_2 \cdot IMA_{it} + \epsilon_{ijt} \tag{4}$$

where as above ULR_{ijt} is the uninsured loan ratio as defined in equation 2, IMA_{it} is the index of market activity for bank i in period t, $ctryconc_{ij^ct}$ is a measure of country concentration, capturing how much of the lending of bank i is to borrowers in country j^c in any given country and time t, and α_i, α_{jt} and α_{it} respectively denote *bank*, $firm \times time$ and $bank \times time$ fixed effects.

Table 3 presents the baseline results. Given that firm characteristics (most notably riskiness) should play a role in the decision to hedge, in all specifications we control for $firm \times time$ fixed effects. In addition, we control for *bank* fixed effects in columns (1) and (2) as well as in columns (4) and (5), and for $bank \times time$ fixed effects in columns (3) and (6). As in Table 2, we observe a positive and statistically significant coefficient estimate on the index of market activity. For the coefficient of the $ctryconc_{ij^ct}$ measure, we find a statistically insignificant point estimate, suggesting that CDS hedging of an individual loan position towards firm j does not depend on the aggregate lending towards other borrowers in the country of firm j. Most importantly, we observe a negative and statistically highly significant coefficient for the CCyB variable: Banks have a lower share of a loan uninsured the higher the CCyB rate is, an indication they use derivative contracts to reduce risk-weighted assets once a loan becomes more expensive from a capital perspective. This effect survives the inclusion of different fixed effects, even when considering within $bank \times time$ and $firm \times time$ variation (columns (3) and (6)). That is, when comparing two loans at one point in time by the same bank towards virtually identical firms domiciled in two different countries, we find that banks buy more CDS written on the firm domiciled in that country where authorities increased the CCyB rate.

Results could be driven by sample selection issues, in particular whether banks are active at all in the CDS market. In columns (4)-(6) of Table 3 we repeat the structure of the regressions in columns (1)-(3) but restricting the sample further to CDS active banks (i.e. in addition to our baseline considering only CDS traded firms): the results are notably stable and convey a similar picture with regards to bank response to the CCyB. In addition, in Table 4 we further restrict the sample by excluding all observations for which the uninsured loan ratio equals one.[32] The point estimates increase in size as a result of such exclusion, and remain highly statistically significant across specifications. When controlling for for $bank \times time$ fixed effects in addition $firm \times time$ fixed effects, the coefficient estimate is reduced in size by around third.

CCyB announcements. Changes to the CCyB rate typically do not take effect immediately, as there is a lag between announcement and implementation to give banks sufficient time to adjust their capital positions. While the analysis above assumes that banks wait until closer to implementation to engage in CDS protection buying or selling for capital relief purposes, banks may start adjusting their capital planning and risk mitigation strategies immediately after a CCyB rate change is announced. To account for this, we repeat the analysis from above as described in equation 4, but replace the CCyB implementation date with the date when authorities announce the CCyB change.

Table 5 and Table 6 present the results for the entire sample and focusing on observations where $ULR \neq 1$, respectively. The tables are order similarly to Table 3 and Table 4. That is, we show in Table 5, columns (1)-(3) results for all CDS traded firms, while columns (4)-(6) concentrates on CDS active firms. The results are qualitatively similar to the main results in Table 3. Quantitatively, we observe a smaller point estimate for the coefficient of the CCyB variable, suggesting that banks make use of CDS for capital relief only when a loan starts to become more expensive.

[32]By construction, this sample contains only CDS traded firms and CDS active banks similar to columns (4)-(6) in Table 3.

Bank Heterogeneity. As a next step, we investigate the heterogeneity of banks with respect to their hedging behavior following a CCyB rate change. In particular, we exploit whether banks are more likely to hedge a loan after an increase in the CCyB rate if they already have a large loan exposure towards the CCyB-setting country, as described in the following regression equation:

$$ULR_{ijt} = \alpha_{it} + \alpha_{jt} + \alpha_{it} + \beta_1 \cdot CCyB_{jt} + \beta_2 \cdot CCyB_{jt} \cdot loanstoctry_{ij^ct} + \gamma_1 \cdot loanstoctry_{ij^ct} + \gamma_2 \cdot ctryconc_{ij^ct} + \epsilon_{ijt}, \quad (5)$$

where $loanstoctry_{ij^ct}$ captures, in addition to the country concentration measure, for each bank i, the sum of loans given to country of firm j at time t. Note that we demeaned the variable *loanstoctry* to allow for a better interpretation of the coefficient. This variable thus captures the (lower bound of the) amount of assets that would be affected by a CCyB change in country where firm j is domiciled. All other variables are defined as before.

The results are shown in Table 7 (CCyB implementation) and Table 8 (CCyB announcement). The coefficients of the variables capturing the index market activity are as before, that is, we observe a positive and significant coefficient, indicating less single-name hedging the more a bank is using index hedges. For the CCyB variable, we find a negative and statistically highly significant coefficient, indicating that banks with an average loan exposure towards country j respond to CCyB changes of country j by buying CDS protection on borrowers domiciled in this country j.[33] On the interaction of the CCyB measure with the *loanstoctry* variable, we observe a negative and significant coefficient, indicating that banks particularly reduce risk-weighted assets using CDS for borrowers in countries where the bank has a large credit exposure after a CCyB change.

[33] Note that we demeaned the variable *loanstoctry* to allow for a better interpretation of the coefficient of the *ccyb* variable.

4 Conclusion

This paper provides novel evidence on how banks use credit derivatives to manage their regulatory capital constraints. We show that in response to an increase in CCyB requirements, banks increase their hedging via credit default swaps (CDS), which carries positive effects in terms of risk-weighted assets. This finding holds even when comparing the behavior of the same bank toward similar firms in different countries within a month, offering compelling causal evidence that complements the literature documenting reductions in lending.

Our results inform discussions about bank responses to macroprudential policy. A liquid CDS market does not merely facilitate credit supply by allowing risk transfer; it also functions as a tool for regulatory capital optimization. This has dual implications. On the one hand, it suggests that the negative impact of tighter capital requirements on credit supply to the real economy might be mitigated, as some banks can adjust their capital ratios without necessarily cutting loans (provided CDS on specific firms are available). On the other hand, it raises important questions about the effectiveness of capital buffers if their constraining effect on bank risk-taking can be circumvented through derivatives markets.

Our findings point to interest avenues for future work. First, it would be valuable to investigate whether hedging behavior leads to a reallocation of credit within the banking sector, from banks that heavily use CDS to those that do not. Relatedly, the impact on lending might be a function of firm size and the attendant availability of CDS to hedge. Second, further work could assess the aggregate, system-wide effects of widespread CDS usage for capital relief and whether it influences the pricing and liquidity of the CDS market. Finally, understanding the post-trade life-cycle of these hedges – whether they are held to maturity or dynamically managed – is crucial for assessing their true risk-reducing properties.

Our paper underscores the multifaceted and sophisticated response of banks to regulation. Policymakers designing macroprudential tools must consider not only the direct impact on bank balance sheets but also indirect effects operating through modern financial markets, where instruments like CDS can alter the transmission of regulatory measures.

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Table 2: Hedging and bank/firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$IMA_{i,t}$	0.0610***		0.0384	0.0677***	0.0650***	0.0665***	0.0655***	0.0727***	0.0665**
	(2.93)		(1.57)	(2.70)	(2.61)	(2.61)	(2.62)	(2.79)	(2.57)
$CDS_{j,t-1}$		-0.000132	-0.000136						
		(-0.77)	(-0.77)						
$LEV_{i,t-1}$				54.09***					67.79***
				(2.69)					(2.83)
$LIQ_{i,t-1}$					0.00356**				0.00427**
					(2.10)				(2.58)
$ROA_{i,t-1}$						-0.269			-0.502
						(-0.79)			(-1.59)
$Tier1_{i,t-1}$							0.0358		-0.0700
							(0.41)		(-0.74)
$Size_{i,t-1}$								-0.835	-0.245
								(-1.25)	(-0.34)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	No	No	No	No	No	No
Firm#Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.219	0.226	0.227	0.340	0.339	0.339	0.339	0.339	0.340
N	60694	36218	36218	51917	52130	52130	51917	52130	51917

This table presents regression estimates for Equation 3. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's hedging activity. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. Control variables include LEV (leverage, defined as Tier 1 capital over total assets), LIQ (liquid assets over deposits and short-term funding), ROA (return on average assets), Tier 1 (core equity capital to total risk-weighted-assets), and Size (log of total assets). $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). $CDS_{j,t-1}$ stands for the lagged CDS spread of firm j, which captures firm riskiness. All variables are lagged by one period except for $IMA_{i,t}$. The sample includes those firms for which there is a CDS available during November 2017 and April 2024, excluding observations where $ULR = 1$. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 3: Banks' responses to countercyclical buffers

	(1)	(2)	(3)	(4)	(5)	(6)
$IMA_{i,t}$	0.00177***			0.00311***		
	(2.89)			(3.10)		
$ccyb_{j,t}$	-50.47***	-50.81***	-50.82***	-51.75***	-52.36***	-53.92***
	(-27.12)	(-27.56)	(-24.54)	(-13.62)	(-13.91)	(-16.90)
$ctryconc_{i,j,t}$	0.0293	0.0288		0.0762	0.0745	
	(0.99)	(0.97)		(0.92)	(0.90)	
Bank FE	Yes	Yes	No	Yes	Yes	No
Bank#Time FE	No	No	Yes	No	No	Yes
Firm#Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.178	0.178	0.191	0.195	0.195	0.207
N	309499	309499	300631	227529	227529	226914

This table presents regression estimates for Equation 4. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccyb* captures the effective (i.e. implemented) countercyclical capital buffer in the country of firm j at time t. *ctryconc* is a measure of the country concentration of lending of bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. IMA stands for a proxy measure for index market activity for bank i at time t (defined in main text). Columns (1)-(3) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024); columns (4)-(6) constrain the sample to CDS active banks (i.e. those banks who engage in either buying or selling of CDS protection at least once during our sample). The sample for all regressions includes observations where $ULR = 1$. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 4: Banks' responses to countercyclical buffers: excluding $ULR = 1$

	(1)	(2)	(3)
$IMA_{i,t}$	0.0658***		
	(2.65)		
$ccyb_{j,t}$	-308.9***	-333.1***	-206.6***
	(-6.35)	(-7.10)	(-5.53)
$ctryconc_{i,j,t}$	-1.327	-1.414	
	(-1.26)	(-1.34)	
Bank FE	Yes	Yes	No
Bank#Time FE	No	No	Yes
Firm#Time FE	Yes	Yes	Yes
R^2	0.338	0.337	0.366
N	52813	52813	52506

This table presents regression estimates for Equation 4. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccyb* captures the effective (i.e. implemented) countercyclical capital buffer in the country of firm j at time t. *ctryconc* is a measure of country concentration of lending by bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. IMA stands for a proxy measure for index market activity for bank i at time t (defined in main text). Columns (1)-(3) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024). The sample for all regressions excludes observations where $ULR = 1$. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 5: Banks' responses to countercyclical buffers: CCyB announcements

	(1)	(2)	(3)	(4)	(5)	(6)
$IMA_{i,t}$	0.00178***			0.00311***		
	(2.90)			(3.10)		
$ccybann_{j,t}$	-18.56***	-18.69***	-19.54***	-18.26***	-18.50***	-20.69***
	(-16.25)	(-16.42)	(-16.61)	(-8.04)	(-8.19)	(-11.37)
$ctryconc_{i,j,t}$	0.0292	0.0287		0.0761	0.0745	
	(0.98)	(0.97)		(0.92)	(0.90)	
Bank FE	Yes	Yes	No	Yes	Yes	No
Bank#Time FE	No	No	Yes	No	No	Yes
Firm#Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.178	0.178	0.191	0.195	0.195	0.207
N	309499	309499	300631	227529	227529	226914

This table presents regression estimates for Equation 4. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccybann* captures the announced countercyclical capital buffer (i.e. not implemented) in the country of firm j at time t. *ctryconc* is a measure of country concentration of lending by bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. IMA stands for a proxy measure for index market activity for bank i at time t (defined in main text). Columns (1)-(3) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024); columns (4)-(6) constrain the sample to CDS active banks (i.e. those banks who engage in either buying or selling of CDS protection at least once during our sample). The sample for all regressions includes observations where $ULR = 1$. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 6: Banks' responses to countercyclical buffers: CCyB announcements excluding $ULR = 1$

	(1)	(2)	(3)
$IMA_{i,t}$	0.0658***		
	(2.65)		
$ccybann_{j,t}$	-154.4***	-166.5***	-103.3***
	(-6.35)	(-7.10)	(-5.53)
$ctryconc_{i,j,t}$	-1.327	-1.414	
	(-1.26)	(-1.34)	
Bank FE	Yes	Yes	No
Bank#Time FE	No	No	Yes
Firm#Time FE	Yes	Yes	Yes
R^2	0.338	0.337	0.366
N	52813	52813	52506

This table presents regression estimates for Equation 4. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccybann* captures the announced countercyclical capital buffer (i.e. not implemented) in the country of firm j at time t. *ctryconc* is a measure of country concentration of lending by bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. IMA stands for a proxy measure for index market activity for bank i at time t (defined in main text). Columns (1)-(3) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024). The sample for all regressions excludes observations where $ULR = 1$. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 7: Banks' responses to countercyclical buffers: exploring bank heterogeneity

	(1)	(2)	(3)	(4)
$ctryconc_{i,j,t}$	4.021**	0.0864**	4.021**	0.372**
	(2.19)	(2.17)	(2.19)	(2.53)
$ccyb_{j,t}$	-628.1***	-56.45***	-628.1***	-69.17***
	(-5.12)	(-14.32)	(-5.12)	(-8.21)
$loanstoctry_{i,j,t}$	-0.0783***	-0.00147*	-0.0783***	-0.00539***
	(-3.72)	(-1.67)	(-3.72)	(-2.63)
$ccyb_{j,t} \times loanstoctry_{i,j,t}$	-25.44**	-0.958*	-25.44**	-2.056*
	(-2.23)	(-1.73)	(-2.23)	(-1.77)
Bank#Time FE	Yes	Yes	Yes	Yes
Firm#Time FE	Yes	Yes	Yes	Yes
R^2	0.369	0.191	0.369	0.208
N	52506	300631	52506	226914

This table presents regression estimates for Equation 5. The dependent variable, ULR_{ijt} of bank i, firm j, time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccyb* captures the effective (i.e. implemented) countercyclical capital buffer (i.e. not implemented) in the country of firm j at time t. *ctryconc* is a measure of the concentration of lending of bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. *loanstoctry* captures, for each bank i, the sum of loans given to country of firm j at time t. Note that we demeaned the variable *loanstoctry* to allow for a better interpretation of the coefficient of the ccyb variable. The sample reflects CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024). Columns (1)-(2) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024); columns (3)-(4) constrain the sample to CDS active banks (i.e. those banks who engage in either buying or selling of CDS protection at least once during our sample). Columns (1) and (3) in turn exclude observations where $ULR = 1$, whereas columns (2) and (4) include such observations.Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

Table 8: Banks' responses to countercyclical buffers: additional robustness with announced CCyB

	(1)	(2)	(3)	(4)
$ctryconc_{i,j,t}$	4.559**	0.0942**	4.559**	0.406***
	(2.50)	(2.33)	(2.50)	(2.71)
$ccybann_{j,t}$	-407.7***	-24.07***	-407.7***	-34.30***
	(-4.29)	(-8.92)	(-4.29)	(-5.43)
$loanstoctry_{i,j,t}$	-0.0821***	-0.00154*	-0.0821***	-0.00572***
	(-3.92)	(-1.73)	(-3.92)	(-2.75)
$ccybann_{j,t} \times loanstoctry_{i,j,t}$	-23.38**	-0.858*	-23.38**	-2.051**
	(-2.38)	(-1.78)	(-2.38)	(-2.09)
Bank#Time FE	Yes	Yes	Yes	Yes
Firm#Time FE	Yes	Yes	Yes	Yes
R^2	0.370	0.191	0.370	0.208
N	52506	300631	52506	226914

This table presents regression estimates for Equation 5. The dependent variable, ULR_{ijt} of bank i, firm j, at time t, as defined in Equation 2, captures a bank's uninsured loan ratio. Values of ULR_{ijt} larger than 1 indicate increased exposure to credit risk (doubling down), while values less than 1 reflect hedging, including negative values which imply over-insurance (net protection exceeding loan exposure). When $ULR_{ijt} = 1$, banks are neither buying or selling (on net) protection on firm j. $IMA_{i,t}$ stands for a proxy measure for a bank's index market activity (defined in the main text). *ccybann* captures the announced countercyclical capital buffer (i.e. not implemented) in the country of firm j at time t. *ctryconc* is a measure of the concentration of lending of bank i at time t, i.e. for a given time t all syndicated lending portfolio by bank i grouped by country of firm j divided by all syndicated lending portfolio by bank i. *loanstoctry* captures, for each bank i, the sum of loans given to country of firm j at time t. Note that we demeaned the variable *loanstoctry* to allow for a better interpretation of the coefficient of the ccyb variable. IMA stands for a proxy measure for index market activity for bank i at time t (defined in main text). Columns (1)-(2) reflect the sample of CDS traded firms (i.e. those firms for which there is a CDS available between November 2017 and April 2024); columns (3)-(4) constrain the sample to CDS active banks (i.e. those banks who engage in either buying or selling of CDS protection at least once during our sample). Columns (1) and (3) in turn exclude observations where $ULR = 1$, whereas columns (2) and (4) include such observations. Robust standard errors in parenthesis. Clustering is at the firm level. ***, **, * respectively indicate statistical significance at the 1, 5 and 10% level.

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