Essays in Banking and Financial Regulation

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Preface

Data by the World Bank shows that the worldwide ratio of domestic credit provided to the private sector – consisting of firms and households – relative to GDP has risen from under 80% in 1980 to 148% in 2020.[1] The Locational Banking Statistics (LBS) by the Bank for International Settlements (BIS) display a 30-fold nominal increase, during the same time, in the cross-border positions of the global banking system.[2] Moreover, claims by the financial sector on governments have increased from 12% to 41% of GDP as the World Bank further reports.[3] The Financial Stability Board's (FSB) Global Monitoring Report on Non-Bank Financial Intermediation further shows that the share of global financial assets held outside of the banking sector has almost reached 50% in 2020.[4]

These data points document several stylized facts. First, not only is the financial sector an integral component of the world economy, but its size surpasses real economic activity by a significant margin. Second, banks and other financial intermediaries are not confined by country borders. Their cross-border activities are meaningful in size and result in tight linkages spanning different economic and regulatory systems. Third, governments and banks are becoming more and more interconnected. Lastly, provision of credit to the economy is a function that is no longer solely fulfilled by banks, but is spread across a large variety of financial institutions.

Due to the enormous importance of credit for economic growth (cf., e.g., Levine [2005]) and, at the same time, the peril of financial crises causing a real economic slump (cf., e.g., Schularick and Taylor [2012]), banks and financial markets, in general, are strongly regulated. In particular, the foundation of the Basel Committee on Banking Supervision (BCBS) in 1974 and many other international bodies, such as the FSB or the

[1] The data can be found here.
[2] The data can be found in Table A1-S on the BIS Website.
[3] The data can be found here.
[4] The report can be found here.

Committee on the Global Financial System (CGFS), constitute big efforts by the global regulatory community to exchange experiences and coordinate policies.

This dissertation aims at connecting the dots between the stylized facts of the financial system and how they interact with the regulatory environment. For this purpose, Chapter 1 analyzes the patterns and economic implications of the opacity of lending portfolios of large European banks. Chapter 2 specifically analyzes the importance of cross-border complexity of banks for their riskiness and sensitivity to regulatory actions. Chapter 3 documents the importance of fiscal capacity and appropriate government interventions in the banking sector during financial crises. Chapter 4 shows how changing the regulatory environment of one component of the financial system – the derivative market – can have important spillover effects to other components – the corporate bond market – which affects firms' financing both quantitatively and qualitatively.

In more detail, Chapter 1, which is joint work with Stefan Avdjiev (BIS), utilizes a rich data set on the composition of large European banks' lending portfolio to generate estimates about the opacity of said portfolio to external investors. I document that asset markets react strongly to public data releases about the portfolio composition highlighting the absence of this information from investors' information set. By slicing the data along several dimensions, I show that opacity is highest for exposures to the sovereign sector held by banks from the European periphery and for exposures to the non-bank private sector held by banks from the European core. In the second part of the analysis, I find that underestimation of banks' credit risk – resulting from incomplete information about banks' portfolios – is associated with lower funding costs and higher wholesale borrowing. Banks from the European core use this additional funding to hoard debt securities while banks from the European periphery use it to (successfully) search-for-yield in the lending market. Given the increasing size and complexity of the financial sector – as documented in the stylized facts – and the potential disciplining effects of pricing on markets, an understanding of the information set of market participants seems crucial in assessing the necessity of regulatory interventions for the dissemination of information about banks' portfolios.

Chapter 2, which is joint work with Iñaki Aldasoro and Bryan Hardy (both BIS), makes use of a unique data set about the geographic spread of the affiliate network of the largest bank holding companies in the world. The descriptive findings mirror very closely the second stylized fact mentioned above: large banks are acting extremely global and their affiliate network is often spread across dozens of countries. By summarizing the information about the geographic complexity of banks' affiliate network in a Hirschmann-Herfindahl type index, I can analyze the relevance of geographic complexity for banks' riskiness. On the one hand, I find that banks with a larger geographic complexity are able to better absorb local economic shocks (meaning less risk), especially when they are present in countries which exhibit a low correlation of their business cycles. On the other hand, the results also show that banks with a larger geographic complexity are able to circumvent prudential regulatory measures (meaning more risk), especially when they are present in countries with weak legal/regulatory systems. I therefore document that geographic complexity has a Janus face, decreasing some but increasing other aspects of bank risk. In the light of the second stylized fact, this paper therefore helps to understand the relevance of cross-border activities in the financial sector both for the (crisis) risk it potentially poses and for the prescription and global coordination of prudential regulatory policies.

Chapter 3, which is joint work with Viral Acharya (NYU Stern School of Business), Lea Borchert (ING) and Sascha Steffen (Frankfurt School of Finance & Management), deals with government interventions in the European banking sector during the Great Financial Crisis. I find that countries with limited fiscal capacity, predominantly located in the European periphery, did not recapitalize their troubled banking sector but instead just provided guarantees to maintain trust in the credit business. The results show that this approach, which is less costly because governments do not need to provide funds to the banking sector ex-ante, resulted in weaker credit supply by banks overall, an increase in zombie lending, a shift from loans to risky sovereign debt and, eventually, a greater reliance on ECB liquidity support in the subsequent Sovereign Debt Crisis. I therefore term this behaviour by governments "kicking the can down the road", because the funds that they did not provide ex-ante had to be provided ex-post to stabilize the economy and to finance ECB's liquidity injections. Related to the third stylized fact, this paper highlights two important of the many facets of the bank-sovereign nexus. First, government interventions in the banking sector – be they of monetary or regulatory nature – have the potential to make a big difference in real economic outcomes. Second, setting the wrong incentive for banks regarding the purchase of government debt causes a strong entanglement between sovereigns and the financial sector, possibly leading to adverse consequences as observed in the aftermath of the European Sovereign Debt Crisis.

Chapter 4, which is joint work with Frederick Zadow (Bundesbank), investigates the consequences of a reform of credit derivative markets for the debt composition of non-financial firms. I analyze a regulatory package making credit derivatives more attractive by reducing counterparty risk on the market they are traded on (central clearing). As there is a no-arbitrage condition between credit derivative and corporate bond markets – two markets that allow trading the default risk of the underlying firm –, this incentivizes traders to leave the corporate bond market and enter the credit derivative market. That is, firms whose credit derivatives are available on the regulated, safer market platform observe a reduction in the demand for their debt. Affected firms try to compensate by demanding more bank loans. While partially successful, insufficient credit supply by banks results in an aggregate loss of external finance for the firms. This has consequences for real economic activity as investment drops and profitability falls. Consistent with the fourth stylized fact, this paper highlights the substitutability between bank and non-bank debt for firms. Small changes to the regulatory environment of the financial system as a whole can lead to shifts in the relative attractiveness of various parts of the system. A holistic understanding of these linkages and spillovers is a research agenda for the future.

Chapter 1

Bank opacity - patterns and implications

Joint with Stefan Avdjiev (Bank For International Settlements).

1.1 Introduction

How well are financial market participants informed about banks' exposures and the associated credit risk? How large is the informational asymmetry between bank outsiders and bank insiders? How does bank opacity affect banks' CDS spread and equity prices? What are the most opaque portions of banks' balance sheets? What are the implications of bank opacity for banks' funding costs, risk-taking and profitability? We examine the above questions by combining a novel event study methodology with a rich dataset that contains detailed information on the geographical and sectoral distributions of the exposures of 130 European banks between 2012 to 2018.

We formulate and examine three sets of hypotheses regarding financial markets' reactions to disclosures of new information on bank exposures. First, in the presence of imperfect information, releasing new data on bank exposures should reduce overall uncertainty, thereby increasing banks' stock prices and decreasing their CDS spreads. Second, if markets are also not perfectly informed about banks' expected loss levels, public releases of new information should also have a directional impact on asset prices. That is, new information that updates market participants' priors towards higher (lower) levels of bank risk should drive stock prices down (up) and CDS spreads up (down). Third, the above directional impact of new information should be greater for CDS spreads than for stock prices. Intuitively, higher risk-taking tends to go hand-in-hand with higher expected returns. In the case of equity prices, these two effects tend to offset each other.

By contrast, in the case of CDS spreads, the second effect is virtually non-existent since higher expected returns affect debt claims only to the extent that they reduce the probability of the bank becoming insolvent.

We test the above hypotheses by employing our novel event study methodology to examine the reactions of bank equity prices and CDS spreads to six public data releases on banks' exposures, done by the European Banking Authority (EBA) between 2014 and 2018. In contrast to standard event study methodologies, we estimate not only the stand-alone impact of the examined event (i.e. the information release) itself, but also the impact of event-triggered changes in an economically meaningful variable (banks' estimated expected losses).

We construct a bank-level estimated expected loss variable (which measures the credit risk inherent in a bank's portfolio) by combining data on the geographical and sectoral distribution of banks' exposures with data on borrowers' credit risk.[1] We obtain data on banks' exposures to individual countries and sectors from the European Banking Authority (EBA) stress testing and transparency exercise databases. We fill the gaps in the EBA data with data from the BIS Consolidated Banking Statistics (CBS). We estimates the credit risk of individual sectors in each country by using either CDS spreads (where available) or the spread between bank lending rates and the corresponding risk-free rates.

The impact of information releases on CDS spreads and equity prices is driven entirely by the exposure component of the expected loss measure rather than by its credit risk component. Market participants have real-time information about (the overall/average levels of) the credit spreads of banks' borrowers. Therefore, changes in the (spread-implied) risk levels of bank borrowers should be continuously incorporated in market participants' estimates of banks' expected losses. By contrast, new public information on banks' exposures arrives (with a substantial lag) only at our event dates. This allows us to cleanly isolate the component of the change in the expected loss estimate that is due to shifts in portfolio composition.

We find strong evidence in support of all of the above hypotheses. First, public releases of any new information on banks' exposures significantly reduced CDS spreads and increased stock prices, highlighting the importance of the uncertainty reduction channel. Second, information revealing that banks' expected losses were higher (lower) than previously estimated, significantly increased (decreased) CDS spreads and de-

[1] Details on the construction of this measure are presented in Section 3.3.

creased (increased) stock prices. This clearly demonstrates that markets correct their prior beliefs about risk levels after the release of new information, which is evidence for the existence of bank opacity. Finally, the reactions of CDS spreads to new information were larger than those of stock prices, in line with our last hypothesis.

After establishing the existence of bank opacity, we dig deeper into its patterns across bank nationalities, borrowing sectors and time periods. First, we show that the reaction of asset markets was much stronger for informational updates regarding sovereign sector exposures than for exposures to the banking or the non-bank private sector. Second, public information releases significantly affected the CDS spreads and equity prices of banks from both, the European core and the European periphery. Third, the effect of new information was strongest for periphery banks' sovereign exposures and core banks' private sector exposures. Fourth, while the uncertainty reduction effect is present throughout our entire sample, the directional effect of new information is only significant in the first half of our sample (from 2014 to 2016).

The above set of results has several important implications. First, they highlight the importance of the bank-sovereign nexus in the immediate aftermath of the European Sovereign Debt Crisis, especially in the European periphery (Acharya et al. [2014]). Second, markets also found value in information on the non-bank private sector exposures of core banks, many of which have lending portfolios spread across a number of countries (cf. Aldasoro et al. [2022]). Last but not least, the greater significance of the results in the first half of our sample suggests that the accumulation of multiple data releases over time allowed market participants to learn about the dynamic patterns of banks' exposures. This improved the accuracy of their assessment of banks' credit risk.

In the final part of our analysis, we investigate the consequences of bank opacity. We first document that deviations of banks' actual credit risk from public information based estimates of their credit risk, were *not* reflected in banks' wholesale funding rates. This implies that MMFs had no superior information over other bank debt and equity investors. At the same time, we also find that banks whose credit risk was underestimated by markets (i.e. banks that faced favorable funding conditions) obtained higher wholesale funding volumes. We use a Khwaja and Mian [2008]-type approach by controlling for Fund $\times$ Time fixed effects to filter out MMF supply effects, which allows us to conclude that the higher wholesale funding volumes were a demand-driven outcome. Thus, it appears that banks which were aware of their (un)favorable funding conditions, demanded more (less) wholesale funding.

In addition, we also investigate whether bank opacity affects banks' asset composition and performance. The first piece of the analysis focuses on syndicated loans to the non-bank private sector, taken from the Dealscan database. While there were no significant effects on bank loans to the non-bank private sector for the full sample, we find that periphery banks whose credit risk was underestimated by markets engaged in riskier lending. Once again, we isolate the bank side of the market, in this case their loan supply, by controlling for Borrower $\times$ Time fixed effects. Furthermore, we find that, while bank opacity had no effect on loan volumes, it was linked to higher debt securities holdings by core banks. Thus, the additional wholesale funding that banks with underestimated credit risk obtained was used quite differently by core and periphery banks - while the former parked it in debt securities, the latter used it to search for yield. Last but not least, we document that periphery banks' risky lending translated into higher net interest margins, while the debt securities investment of core banks did not.

Related literature. Our findings on general and directional bank opacity add to the strand of literature dealing with bank opacity and the market disciplining effects of information disclosures, in particular through stress test exercises.

From a theoretical perspective, Goldstein et al. [2014] and Goldstein and Leitner [2018] go through several potential impact channels of information disclosures of stress test results. The authors conclude that the effects for individual institutions can be heterogeneous. We add further evidence that the disclosure of information can have both positive or negative effects for each bank, depending on whether the market was previously over- or underestimating that bank's credit risk. Empirically, Flannery et al. [2017] and Morgan et al. [2014] show that there are significant market reactions to information disclosures related to bank stress tests in the US. While our results are qualitatively in line with theirs, our methodology differs by directly linking the bank-specific informational content of the release to the size and direction of the asset price return. For Europe, Sahin and De Haan [2016] document little market reaction to the stress test results published in 2014, while Petrella and Resti [2013] focuses on the stress test results published in 2011 and show strong market reactions. In spirit and methodology, Petrella and Resti [2013] is closest to the part of our study investigating the EBA data releases. We examine the EBA data releases more structurally than these authors in two aspects. First, we investigate all six data releases that took place between 2014 and 2018 (instead of just a single one) in order to identify more systematic and statistically robust patterns. Second, our methodology goes a step further in identifying the (bank-specific) informational value of each data release. Instead of just identifying a reaction to positive or negative news, we link the market reaction to changes in the portfolio composition of each bank.

Theoretical studies such as Heider et al. [2015] have highlighted the adverse impact of asymmetric information about credit risk on banks' liquidity costs (i.e. funding costs). We add an empirical piece of evidence to these analyses, suggesting that asymmetric information does adversely affect banks' funding costs if their credit risk exposure is overestimated by markets. Importantly, we also document that an underestimation of credit risk results in lower funding costs for those banks. The evidence for such a two-sided effect is a novelty in the empirical literature and ties into the theoretical considerations by Goldstein et al. [2014], who conjectured variation in the bank-specific effects of opacity. Our results that banks which are perceived as riskier obtain less (wholesale) funding mirror recent empirical findings by Pérignon et al. [2018] or Imbierowicz et al. [2021].

Finally, we link the level of bank opacity and the associated funding cost distortions to banks' asset allocation decisions. Banks' lending decisions (choice of assets) are closely linked to their funding mix (composition and cost of liabilities), so that they will either reduce (risk-weighted) assets or search for yield if capital is scarce (Acharya et al. [2021], Jiménez et al. [2017]; others) or debt funding costs are high (Heider et al. [2019]).[2] We document that banks that obtain additional funding due to an underestimation of their credit risk search for yield in the loan market (if they are from the European periphery) or increase their debt securities holdings (if they are from the European core).[3]

Roadmap. The remainder of this paper is structured as follows. Section 3.3 provides information on the data sources and the construction of our key variables. Section 1.3 presents our event study analysis that documents the existence and patterns of bank

[2] We intentionally do not relate our findings to the literature on the bank-lending channel of monetary policy. The debt funding cost distortions that we document are not driven by a policy decision, but are a general feature of the informational characteristics of asset markets.

[3] The relationship between bank opacity and risk taking has been examined theoretically by Jungherr [2018] and empirically by Fosu et al. [2017]. The general relationship between bank opacity and lending is investigated by Zheng [2020]. Hau and Lai [2013] show that underpricing of non-financial firms' stocks (analogous to overestimation of credit risk in our setting) is associated with lower investment activity.

opacity. Section 1.4 presents our empirical analysis of the implication of bank opacity. Section 4.7 concludes.

1.2 Data

1.2.1 Key variables - definitions and sources

The main building block of our analysis is the measure that we use to quantify the credit risk in banks' exposures to individual sectors in each country:

$$CSEL_{i,j,k,t} = \frac{EAD_{i,j,k,t} \cdot PD_{j,k,t} \cdot LGD_{j,k,t}}{TC_{i,t}}, \tag{1.1}$$

where $CSEL_{i,j,k,t}$ is the expected loss of bank i, on its exposures to sector k in country j at time t; $EAD_{i,j,k,t}$ is the Exposure at Default (measured in nominal (Euro) terms) of bank i on its exposures to sector k in country j at time t. $PD_{j,k,t}$ and $LGD_{j,k,t}$ are the average Probability of Default (PD) and Loss Given Default (LGD), respectively, of borrowers from sector k in country j at time t. $TC_{i,t}$ is the Tier 1 capital (measured in nominal (Euro) terms) of bank i at time t.

We use the above granular (borrowing sector/country-specific) expected loss measure to construct the following aggregate (bank-level) expected loss measure:

$$EL_{i,t} = \sum_{j,k} CSEL_{i,j,k,t} \tag{1.2}$$

If market participants rely on publicly released data in order to obtain information about banks' exposures to individual sectors and countries, their estimates of each bank's expected (country/sector-specific) losses can be expressed as:

$$\widehat{CSEL}_{i,j,k,t} = \frac{EAD_{i,j,k,t^*} \cdot PD_{j,k,t} \cdot LGD_{j,k,t}}{TC_{i,t}}, \tag{1.3}$$

where t^* denotes the latest date for which there is publicly available information on the EAD. Table 1.1 lists each t^* date in our sample, along with the corresponding data release dates (T).

Table 1.1: Event dates

Data Release	T_m	t^*_m
0	December 16, 2013	June 30, 2013
1	October 26, 2014	June 30, 2014
2	November 25, 2015	June 30, 2015
3	July 29, 2016	December 31, 2015
4	December 2, 2016	June 30, 2016
5	November 24, 2017	June 30, 2017
6	November 2, 2018	June 30, 2018

Note: This table displays the public data release dates (T) in our sample and the corresponding "latest available" dates (t^*) for which data was published in each case.

In turn, market participants' estimates of aggregate (bank-level) expected losses are given by:

$$\widehat{EL}_{i,t} = \sum_{j,k} \widehat{CSEL}_{i,j,k,t} \tag{1.4}$$

In addition, we also define a variable that captures the gap between actual expected losses ($EL_{i,t}$) and estimated expected losses ($\widehat{EL}_{i,t}$):

$$EL\_Gap_{i,t} = EL_{i,t} - \widehat{EL}_{i,t} \tag{1.5}$$

The main source for constructing the EAD variable are the data from the transparency exercises and stress tests of the European Banking Authority (EBA).[4]

These EBA data contain information about each bank's credit risk exposures, broken down by the country and the sector of the counterparty. The EBA discloses each bank's exposures to the ten countries to which it is most exposed and breaks them down into several sectoral counterparty categories. The main sectoral categories on which we focus in this study are "General Government" (which we call *Sovereign Sector*), "Institutions" (which we label *Banking Sector*), "Corporates" and "Retail" (which we combine into the *Non-Bank Private Sector (NBPS)*). We complement the EBA data with information

[4]The EBA has been publishing these semi-annual data for a large set of European banks since 2013. A substantial amount of the data collected for these exercises are publicly available on the EBA website, but are published with a time lag. More concretely, the data for H2 of year t and H1 of year $(t+1)$ are released in Q4 of year $(t+1)$. For example, the data for 2016H2 and 2017H1 were released in 2017Q4.

obtained from the Consolidated Banking Statistics (CBS) of the Bank for International Settlements (BIS). More concretely, we use the BIS CBS to impute the data points that are not reported by the EBA (ie the data on each bank's exposures to borrowers from countries that are outside the respective top 10 list covered by the EBA). For a more detailed description of this imputation see Appendix 1.A.1.

Following Hull [2003], we compute the PD of borrowers from sector k in country j at time t using the following the formula:

$$PD_{j,k,t} = 1 - exp(-Spread_{j,k,t} * Mat), \tag{1.6}$$

where Mat is the maturity of the contract for which the spread is given, e.g. 5 years for a 5-year sovereign CDS contracts and $Spread_{j,k,t}$ is the credit spread of borrowers from sector k in country j at time t.[5] We construct the spreads data series by combining information from several different sources, depending on the sector. For the *Sovereign Sector*, we use 5-year sovereign CDS spreads from Markit. For the *Banking Sector*, we follow Avdjiev et al. [2019] and use an asset-weighted average of the 5-year CDS spreads (obtained from Markit) of the largest banks headquartered in the respective borrowing country.[6] The literature has shown that movements in CDS spreads primarily reflect variations in the markets' perception of the underlying entity's default risk (see Longstaff, Mithal, and Neis, 2005). Finally, we construct the spreads for the *Non-Bank Private Sector* as the difference between the borrowing rates of private non-financial borrowers (non-financial corporations and households) in each country (obtained from various sources, including the ECB, the Fed and other central banks) and the yield of the 10-year German government bond (as a proxy for the "risk-free rate" in the euro area).[7]

In addition, we obtain bank-level data on variables such as total assets, Tier 1 capital ratio, net interest margin, loan loss reserves, and others from SNL Financial. We

[5] The above formula assumes a constant recovery rate. Since we have no data on recovery rates, we set all of them to zero. Our results are not sensitive to this assumption. The above formula also assumes a Poisson process for the default incident and independence of the default event and the term structure.

[6] We use this measure since large banks account for the overwhelming majority of cross-border interbank activities and domestic interbank networks are often centralized at a few big institutions (Demirer, Diebold, Liu, and Yilmaz, 2018).

[7] In order to have a tractable and conservative estimate of expected losses, we set all LGD values to 100% (for all counterparties across countries and time periods). Using the LGD values put forward in the Standardized Approach for credit risk by the Basel Committee, which vary across sectors, does not affect our main results and conclusions.

collect data on bank CDS spreads from Markit and on bank equity prices from Thomson Reuters' Eikon. We retrieve data on European banks' funding from US MMFs from iMoney. We obtain syndicated loan data from Dealscan and match them to borrower balance sheet information from Bureau van Dijk's Amadeus database.

1.2.2 Data summary

Table 1.2 presents descriptive statistics of the main variables used in our empirical analysis. The expected loss (as a share of Tier 1 capital) variable has an average of 29%, a median of 28% and a standard deviation of 11%. The key summary statistics for the estimated expected loss variable are very close to the their counterparts for the expected loss variable. As a consequence, the average and the mean of the variable capturing the gap between the two expected loss measures are both very close to 0. Nevertheless, the standard deviation (4%) as well as the minimum (-11%) and maximum values (14%) of the expected loss gap variable clearly signal a considerable degree of variation in that variable. We exploit this in our empirical analysis presented in Section 4.

Table 1.2: Descriptive statistics

	Mean	Median	Std. Dev.	Min	Max
$EL_{i,t}$	0.29	0.28	0.11	0.09	1.06
$\widehat{EL}_{i,t}$	0.28	0.28	0.10	0.09	0.59
$EL\_Gap_{i,t}$	0.00	0.00	0.04	-0.11	0.14
$Total\ Assets\ (log)$	19.21	19.06	1.48	14.82	21.99
$Tier1\ Ratio$	0.15	0.13	0.08	0.07	0.65
$ROAA\ (\%)$	0.18	0.23	0.65	-2.33	1.88
$Net\ Interest\ Margin\ (\%)$	1.37	1.28	0.88	-0.01	5.96
$Reserves\ over\ Loans\ (\%)$	3.74	2.00	3.93	0.00	17.00
$Liquid\ Assets\ over\ Assets\ (\%)$	32.00	31.00	14.42	5.00	77.50
$Loan\ Loss\ Provisions\ over\ Loans$	0.01	0.00	0.01	-0.00	0.04
$CDS\ Spread$	148.47	107.49	127.28	1.00	729.38

Note: This table displays descriptive statistics for all banks in our benchmark sample (from 2012Q4 to 2018Q2).

Table 1.2 also summarizes the main distributional parameters for the bank-level control variables employed in our study. The average bank in our sample is relatively large and well-capitalized, with a Tier 1 capitalization ratio of 15%. There is considerable heterogeneity among banks when it comes to their reserves (ranging from 0% to 17% of loans) and liquid assets (ranging from 5 to 78% of assets). Banks' CDS spreads range from nearly zero to just under 730 basis points, with an average of 148 and a median of 107 basis points.

Next, we drill one level deeper into the distribution of banks' expected losses by examining the evolution of their main sectoral components (averaged across the our sample of bank) over time (Figure 1.1a, left-hand panel).[8] The aggregate sectoral shares are relatively stable over time. The majority of banks' credit risk was due to their exposures to the NBP sector, whose shares ranged from 59% to 83%. The respective shares of interbank exposures (between 11% and 23%) and sovereign exposures (between 3% and 18%) were considerably smaller.

In turn, the right-hand panel of Figure 1.1b decomposes the expected loss gap ($EL\_Gap_{i,t}$) into its sectoral components. While the NBP sector still accounts for the largest share of the variance of the expected loss gap variable, its relative importance is considerably smaller than in the decomposition of the expected loss level.[9] The contribution of the NBP sector to the variation in the expected loss gap ranges from 29% to 66%. The corresponding shares for the banking sector are 19%-41%, and 8%-41% for the sovereign sector. Thus, even though exposures to the NBP sector account for the majority of the expected losses in our sample, the expected loss gap is much more evenly spread across sectors. We take advantage of this feature of the data in the empirical analysis we present in Section 1.3.

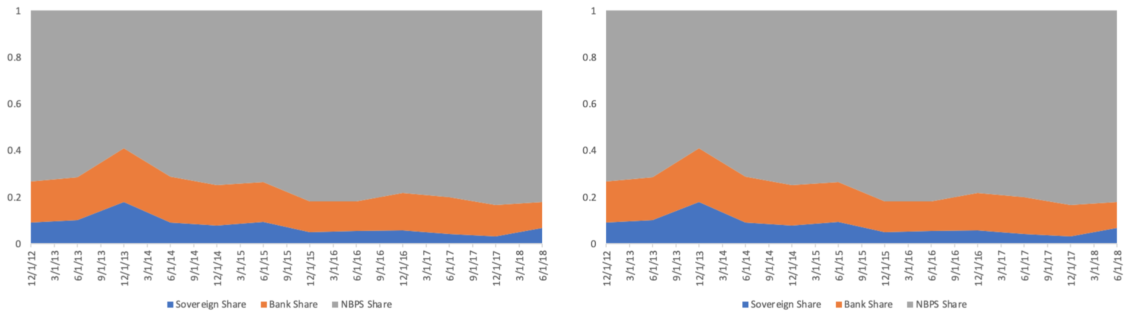
[8]We aggregate $\widehat{CSEL}_{i,j,k,t}$ across all counterparty countries to obtain sector-specific estimated expected losses for each bank at each point in time: $\widehat{SEL}_{i,k,t} = \sum_j \widehat{CSEL}_{i,j,k,t}$.

[9]We generate the decomposition of the expected loss variable by (i) taking the absolute value of the difference between each of its values ($EL\_Gap_{i,t}$) and its period-specific average ($\overline{EL\_Gap_t}$) and (ii) averaging the resulting differences across sectors. The resulting estimates reflect the contribution of each sector to the variation of the expected loss gap over time.

Figure 1.1: Sectoral decompositions

a) Sectoral decomposition of banks' expected losses

b) Sectoral decomposition of banks' expected loss gaps



Note: Panel a) shows the decomposition of the $EL_{i,t}$ variable into its sectoral subcomponents. Panel b) shows the decomposition of the variation in the $EL\_Gap_{i,t}$ variable into its sectoral subcomponents.

1.3 The impact of public information disclosures

1.3.1 An illustrative theoretical model

Before delving into our empirical exercises, we propose a simple illustrative theoretical model in order to fix ideas regarding the expected impact of public information disclosures (in the presence of bank opacity) on the prices of banks' equity prices and CDS spreads.

Consider a bank that is funded by a continuum of risk-averse debt and equity investors. Buying a unit of the bank's debt claims yields the following payoff structure: if the bank defaults, the investor receives 0; if the bank does not default, the investor receives $1 + r_f$. Assuming the bank defaults with probability PD, the expected gross payoff equals $(1 - PD)(1 + r_f)$. Without loss of generality, assume $r_f = 0$.
While the bank's default probability (PD) is not publicly known (due to bank opacity), investors have (incomplete) information about it. Their prior belief about PD has a normal distribution with mean $\overline{PD}$ and standard deviation σ.

Let the utility of an investor from payoff p_1 and price p_0 be given by:

$$U(p_1) = -e^{-\lambda(p_1 - p_0)}; \lambda > 0. \tag{1.7}$$

This exponential utility function fulfils the Arrow-Pratt definition of constant absolute risk aversion (CARA) with risk aversion coefficient λ.

The equilibrium price of a bank's debt claim in $t = 0$ is $p_0 = (1 - \overline{PD}) - \frac{\lambda}{2}\sigma^2$.[10] This equilibrium price of the debt claim contains three components: (i) the price of a risk-free asset in a perfect information world (1), (ii) the default-risk discount ($-\overline{PD}$), which compensates investors for the fact that their claims on the bank are not risk-free and (iii) the uncertainty discount ($-\frac{\lambda}{2}\sigma^2$), which compensates investors for the fact that the probability of default is not known with certainty (i.e. for the fact that there is no perfect information).

The equation for the price of a debt claim generates two testable predictions about how the disclosure of new information about a bank's exposures should affects the price of debt claims on that bank. First, any new information about a bank's exposures will reduce investors' uncertainty, thereby increasing the price of debt claims on the bank. Second, information which updates the belief of investors towards a higher (lower) $\overline{PD}$ will decrease (increase) the price of debt claims on the bank.

Meanwhile, we can define the payoffs of an equity claim on the bank as 0 if the bank defaults and $(1 + r_f)(1 + PD)$ if the bank does not default. The additional term in the equity claim payoff in the non-default state of the world relative to the respective debt claim payoff reflects the potential upside of for equity investors associated with the additional return, which is assumed to be proportionate to the bank's default risk. The expected gross payoff then equals $(1 - PD^2)(1 + r_f)$ which translates to an equilibrium price of $p_0 = (1 - \overline{PD}^2) - \frac{\lambda}{2}\sigma^2$.[11] As in the case of the debt claim price, the equilibrium price of the equity claim contains three components: (i) the price of a risk-free asset in a perfect information world (1), (ii) the default-risk discount ($-\overline{PD}^2$) and (iii) the uncertainty discount ($-\frac{\lambda}{2}\sigma^2$).

Analogously to the expression for the debt claim price, the equity price equation generates two testable predictions. First, any new information about a bank's exposures will increase the bank's equity price reducing investors' uncertainty. Second, information which updates the belief of investors towards a higher (lower) $\overline{PD}$ will decrease (increase) the bank's equity price.

Taken together, the above expressions for the equilibrium prices of debt and equity claims on the bank also imply that the sensitivity to new information about the probability of default, measured as $|\frac{\partial p}{\partial \overline{PD}}|$, should be lower for equity claim prices than for debt claim prices, as $\overline{PD} < 0.5$ in virtually all (plausible) cases. Intuitively, new in-

[10]See Appendix 1.B for the proof.
[11]The proof is analogous to the proof for the equilibrium price of debt claims in Appendix 1.B.

formation revealing that a bank's portfolio is riskier than investors previously believed would have two effects. First, it would increase the bank's default probability, which would push its debt and equity prices down. Second, the average yield of the bank's overall portfolio would increase (as a compensation for the higher risk the bank has taken), which would in turn boost the bank's expected profits in "non-default" states of the world. While this second effect would have a positive impact on the bank's equity price, its impact on the price of debt claims would be negligible as long as the bank's capitalisation is sufficiently above the default boundary (since positive news about profitability affect debt claims only to the extent that they reduce the probability of the bank becoming insolvent). Thus, the overall impact of information disclosures on debt pricing (which would typically be influenced only by the first effect) should be greater than the respective effect on equity prices (where the second effect would at least partially offset the first effect).

By interpreting the CDS spread as the wedge (i.e. discount rate) between the price of the risk-free asset and the price of the risky debt claim $(1 - p_0)$ in our illustrative model, we can formalise the above model predictions as the following testable hypotheses:

Hypothesis 1a: *The release of new information about a bank's exposures lowers its CDS spread.*
Hypothesis 1b: *The release of new information about a bank's exposures increases its equity price.*

Hypothesis 2a: *The release of new information revealing that the overall credit risk level in a bank's portfolio is higher (lower) than previously estimated increases (decreases) its CDS spread.*
Hypothesis 2b: *The release of new information revealing that the overall credit risk level in a bank's portfolio is higher (lower) than previously estimated decreases (increases) its equity price.*

Hypothesis 2c: *The release of new information revealing that the overall credit risk level in a bank's portfolio is higher (lower) than previously estimated increases (decreases) the bank's CDS spread by more than it decreases (increases) the bank's equity price.*

Next, we test the above hypotheses by examining the impact of public data disclosures about banks' exposures on their CDS spreads and equity prices.

1.3.2 Empirical framework

In this section, we introduce the empirical setup we use to investigate the impact of public data releases by the European Banking Authority (EBA) about banks' exposures on their CDS spreads and equity prices. If markets are indeed not perfectly informed about banks' exposures ($\sigma > 0$ and/or $\overline{PD} \neq PD$ in the model above), the disclosure of the detailed information by the EBA, should lead to an update of market participants' priors about banks' expected losses and, consequently, to a repricing of banks' CDS spreads and equity prices.

We take the six data releases in our sample (which took place on October 26, 2014; November 25, 2015; July 29, 2016; December 2, 2016; November 24, 2017; and November 2, 2018) and construct the following two variables anchored around each release date (T):

$$\Delta\widehat{EL}_{i,T+l} = \widehat{EL}_{i,T+l} - \widehat{EL}_{i,T-s} \tag{1.8}$$

$$\Delta AP_{i,T+l} = log(AP_{i,T+l}) - log(AP_{i,T-s}). \tag{1.9}$$

where $\Delta\widehat{EL}_{i,T+l}$ is the difference in bank i's estimated expected loss s business days before the data release ($\widehat{EL}_{i,T-s}$) and l business days after the data release ($\widehat{EL}_{i,T+l}$). Since market participants' estimates of the PD and the LGD (of banks' counterparties) are not affected by public disclosures of banks' exposures, the wedge between $\widehat{EL}_{i,T+l}$ and $\widehat{EL}_{i,T-s}$ is entirely due to the gap between the current, but not yet publicly known, exposures and the exposures as of the last public disclosure. In other words, this measure captures the informational difference in the expected loss measure between the two releases due to the portfolio composition. $\Delta AP_{i,T+l}$ captures the growth rate of the CDS spread or the equity price in the (l+s business day) event window (between t-s and t+l) surrounding the data release. In our benchmark empirical exercises, we set s=1 and l=3, so that we capture the asset returns between the closing price on the business day immediately preceding the day of the data release (t-1) and the closing price four business days after the data release (t+3). We have selected this 5-business day (1-week) window as our benchmark because we believe it strikes the optimal balance between being inclusive and being targeted. On the one hand, it is long enough to capture all movements in asset prices induced by the data release (even if it takes the market a few days to digest the newly released information). On the other hand, our benchmark event window is short enough to not be significantly affected by any other major events or public informational releases. Our main results are robust to varying the sample window between 3 and 10 days.[12]

We use the above variables to construct and estimate the following regression:

$$\Delta AP_{i,T+l} = \alpha + \beta \cdot \Delta \widehat{EL}_{i,T+l} + \epsilon_i. \tag{1.10}$$

The coefficients α and β will tell us how markets react to the informational update in the expected loss component.

A negative (positive) α would be in line with Hypothesis 1a and 2a (from Section 2.1), according to which CDS spreads (equity prices) should go down (up) in response to the arrival of new information about banks' exposures since it would lower uncertainty about their expected losses and their PDs. This constant term coefficient is the counterpart to the main object of interest in a typical event study.

The novel aspect that we introduce to the event study methodology is related to the coefficient (β) on the expected loss term. A positive (negative) β in the regressions for CDS spreads (equity prices) would be in line with Hypotheses 2a and 2b, which postulate that new information implying that a bank's expected losses (and, therefore, its credit risk) are higher than the market's estimates would lead to an increase in the bank's CDS spread and a decrease in its equity price. Finally, according to Hypothesis 2c, the absolute magnitude of β should be higher for CDS spreads than for equity prices (since the reaction to new information should be greater for CDS spreads than for equity prices).

In a standard event study setting, one defines a "normal" return (typically derived from a CAPM model) in order to classify returns during the event window as "abnormal" if they deviate from those "normal" returns (e.g. Campbell et al. [1998])). The abnormality of the return can then be attributed to the event. This approach is not optimal in the context of our analysis for two reasons. First, the EBA data disclosures are events with systemic implications because they reveal critically important information about a large set of banks, which account for the majority of the European banking system's assets. As a consequence, the market-wide return triggered by such an event is itself not "normal". Second, the β from Equation 1.10 – a crucial object for testing Hypotheses 2a, 2b and 2c in our study – could be correlated with the CAPM-β, thus inducing an estimation bias when using the CAPM-adjustment of returns. A higher β

[12] The results from these robustness checks are available upon request.

in Equation 1.10 indicates higher opacity, as markets are reacting more strongly to new information. At the same time, the asset prices of a more opaque bank might follow more closely the market return (i.e. exhibit a higher CAPM-β) because (by definition) markets have less bank-specific information on which to base their pricing. In such a case, the two βs would be positively correlated and the estimation would be biased. Thus, in order to avoid the above problems, we do not include a CAPM-adjustment in our benchmark event study methodology.

1.3.3 Baseline results

Table 1.3 summarizes our baseline results for the impact of public information disclosures on CDS spreads (Columns 1-3) and equity prices (Columns 4-6). We estimate three regression specifications for each of the two instruments - without any FEs (columns 1 and 4), with bank FEs (columns 2 and 5) and with time and bank FEs (3 and 6). The results from the baseline regressions are fully in line with the hypotheses presented in Section 3.1.

Consistent with Hypotheses 1a and 1b, we find evidence that the release of any new information on banks' exposures (regardless of how it compares to market participants' prior expectations) decreases uncertainty about banks' expected losses and default probabilities, thereby reducing CDS spreads and increasing equity prices. In the specifications without any FEs (columns 1 and 4, respectively) and with bank FEs (columns 2 and 5, respectively), the constant terms have the expected signs (negative for CDS spreads and positive for equity prices) and strongly statistically significant. As expected, the constant terms are not significant in the specifications that include time FEs (columns 3 and 6, respectively) since the the common impact of the informational releases in each of the respective periods we examine is absorbed by the time FEs.

Moreover, our baseline results also suggest that upward revisions of banks' estimated expected losses, triggered by newly released information about banks' exposures, are associated with increases in CDS spreads and declines in equity prices. This is fully in line with Hypotheses 2a and 2b. In all specifications, the estimated coefficients on the expected loss term are strongly statistically significant with the expected signs (positive for CDS spreads and negative for equity prices).

The results presented in Table 3 also provide evidence in support of Hypothesis 2c, according to which public releases of information should have a greater impact on

CDS spreads than on equity prices. The absolute value of the estimated coefficient on the expected loss terms are consistently greater in CDS spread regressions than in the respective equity price regression (in all specifications that we examine). Intuitively, in the case of equity prices the negative impact of higher expected losses is (at least partially) offset by the positive impact of the higher returns that are associated with investing in riskier assets. There is no such offsetting effect in the case of CDS spreads since banks' debt-holders benefit from positive news about banks' profits only to the extent that it decreases the probability of the bank becoming insolvent. [13]

The estimated effects of the EBA's information releases are not only statistically, but also economically significant. The baseline estimates (in columns (1) and (4) of Table 3) of the constant terms imply a 5% reduction in CDS spreads and a 2% increase in stock prices due to the uncertainty reduction effect of public data disclosures. The estimates of the slope coefficients suggest that a one-standard deviation (0.06) increase in banks' estimated expected losses ($\Delta\widehat{EL}_{i,T}$) is associated with a 3% rise in CDS spreads and a 1.7% fall in stock prices. These numbers are sizeable. For example, a 3% mispricing of the CDS spread of Deutsche Bank would imply a distortion of approximately 4.5 bps. As Deutsche Bank has liabilities of approximately 1.5 trillion Euro, this would translate into additional funding costs of 675 million Euro.[14] Furthermore, given a market capitalization of 20 billion Euro for the same bank, the equity price mispricing would translate to a 340 million Euro distortion.

[13] While the correlation between stock and CDS returns in our sample is negative, it is also relatively low: its median is -0.21 for the full sample and -0.14 for event dates. This suggests that the above results capture separate valuation effects of asymmetric information on both, equity prices and CDS spreads rather than a single effect on only one of those asset prices that mechanically drives the other.

[14] The above calculation is based on the assumption that each basis point increase in CDS spreads translates into one basis point increase in funding costs. This represents a conservative assumption since Imbierowicz et al. [2021] have shown that funding costs tend to increase more than one-to-one with CDS spreads.

Table 1.3: Event study results – baseline

	(1) ΔCDS	(2) ΔCDS	(3) ΔCDS	(4) ΔEquity	(5) ΔEquity	(6) ΔEquity
$\Delta\widehat{EL}_{i,t}$	0.48***	0.58***	0.32***	-0.27***	-0.29**	-0.27**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.03)
Constant	-0.05***	-0.05***	0.03	0.02***	0.02***	-0.00
	(0.00)	(0.00)	(0.21)	(0.00)	(0.00)	(0.77)
R^2	0.10	0.07	0.31	0.11	0.07	0.35
N	172	172	172	172	172	172
Bank FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	No	Yes	No	No	Yes

Note: This table shows the results of estimating the event study regression $\Delta AP_{i,T+l} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,T+l} + \epsilon_i$ on the balanced sample where both a CDS and a equity price are available for every bank. The regression is estimated for six event points: October 26, 2014; November 25, 2015; July 29, 2016; December 2, 2016; November 24, 2017; and November 2, 2018. The Δ is taken between 3 days after ($l = 3$) and one day before the data release. P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. R^2 in panel regressions is within R^2.

1.3.4 Bank opacity patterns

In this subsection, we delve deeper into our benchmark results by examining the extent to which market reactions to informational releases differ along several dimensions. First, we split $\Delta\widehat{EL}_{i,t}$ into its three main sectoral subcomponents: sovereign, bank, and non-bank private sector. This allows us to quantify and compare the relative strength of markets' reactions to new information about banks' expected losses vis-a-vis the main sectors to which they are exposed.

The results from this exercise are summarized in the first three columns of Table 1.4. They reveal that (CDS and equity) markets reacted most strongly to newly released information about banks' sovereign exposures. The estimated coefficients on the sovereign component of the expected loss measure have the expected signs, positive for CDS spreads (Panel A, column 1) and negative for equity prices (Panel B, column 1), and are highly statistically significant. By contrast, the estimated coefficients on new information for the bank and the non-bank private sector components of bank's expected losses are not statistically significant for both CDS spreads (Panel A, columns 2 and 3, respectively) and equity prices (Panel B, columns 5 and 6, respectively).

Next, we examine whether the reaction of markets to new information on banks' expected losses varied between banks from the so-called "core" part of Europe versus banks from the so-called "periphery" part of Europe. For the purposes of this exercise, we define the European "periphery" as consisting of Hungary, Ireland, Italy, Portugal, and Spain.[15] The remainder of the countries in our sample are classified as the European "core".

Columns 4 and 5 of Table 1.4 contain the results for the geographic split of the banks in our sample (European periphery vs. European core). All of our main hypotheses hold for both sets of banks. Releasing public information on exposures (regardless of the direction in which it takes market expectations) decreases CDS spreads and increases equity prices for both groups of banks (in line with hypotheses 1a and 1b). Newly released information that increases market participants' estimates of banks' expected loses, is associated with increases in CDS spreads and declines in equity prices for both, core and periphery banks (in line with hypotheses 2a and 2b). Furthermore, the impact on CDS spreads is greater than the impact on equity prices for both (core and periphery) sub-samples of banks (in line with hypothesis 2c).

Next, we examine the extent to which our main results vary over time. It is possible that the degree of asymmetric information was higher during the immediate aftermath of the European Sovereign Debt crisis. It is also likely that, as the number of EBA data releases kept growing, market participants gradually learned more about banks' portfolio composition patterns. Bischof and Daske [2013] suggested that after the EBA started releasing data, banks increased their voluntary disclosures, too, further accelerating the markets' ability to learn. If those effects are significant, our main results should be stronger in the early half of our sample than in its late half.

In order to examine the above hypothesis, we re-estimate our benchmark regressions on an "early" sub-sample (2013M12 to 2016M7) and a "late" sub-sample (2016M12 to 2018M12). The results from those exercises are presented in Columns (6) and (7) of Table 1.4. The coefficients on the expected loss term in the first ("early") half of the sample are strongly statistically significant and in line with our benchmark results presented in Table 1.3. By contrast, the respective coefficients in the second ("late") half of the sample are not significant. The constant terms – referring to the uncertainty reduction – are highly significant (for both asset classes) in both sub-samples.

[15] We exclude Greek banks from our data set since their CDS spreads and equity prices behave too erratically relative to the rest of our sample.

Table 1.4: Event study results – sector, time and bank nationality splits

Panel A – splits for CDS

	(1) ΔCDS Sectoral	(2) ΔCDS Sectoral	(3) ΔCDS Sectoral	(4) ΔCDS Core	(5) ΔCDS Periphery	(6) ΔCDS Early	(7) ΔCDS Late
$\Delta\widehat{EL}_{i,t}$				0.66***	0.44***	0.51***	0.11
				(0.01)	(0.00)	(0.00)	(0.78)
$\Delta\widehat{SEL}_{i,Sovereign,t}$	0.53***						
	(0.00)						
$\Delta\widehat{SEL}_{i,Bank,t}$		1.45					
		(0.11)					
$\Delta\widehat{SEL}_{i,NBPS,t}$			0.24				
			(0.32)				
Constant	-0.05***	-0.04***	-0.04***	-0.06***	-0.04***	-0.04***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
R^2	0.09	0.02	0.00	0.05	0.16	0.16	0.00
N	172	172	172	100	72	84	88

Panel B – splits for stocks

	(1) ΔEquity Sectoral	(2) ΔEquity Sectoral	(3) ΔEquity Sectoral	(4) ΔEquity Core	(5) ΔEquity Periphery	(6) ΔEquity Early	(7) ΔEquity Late
$\Delta EL^*_{i,t}$				-0.14*	-0.29***	-0.26***	0.05
				(0.06)	(0.01)	(0.00)	(0.82)
$\Delta\widehat{SEL}_{i,Sovereign,t}$	-0.37***						
	(0.00)						
$\Delta\widehat{SEL}_{i,Bank,t}$		0.33					
		(0.64)					
$\Delta\widehat{SEL}_{i,NBPS,t}$			-0.03				
			(0.85)				
Constant	0.02***	0.02***	0.02***	0.03***	0.02**	0.01	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)
R^2	0.15	0.00	0.00	0.02	0.13	0.15	0.00
N	172	172	172	100	72	84	88

Note: Columns (1)-(3) of panel A show the results of estimating the event study regression $\Delta CDS_{i,T+l} = \alpha + \beta \cdot \Delta\widehat{SEL}_{i,k,T+l} + \epsilon_i$. Columns (4) and (5) show the results of estimating the event study regression $\Delta CDS_{i,T+l} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,k,T+l} + \epsilon_i$ separately for banks from the European periphery (ES, HU, IE, IT, PT) and the European core (AT, BE, DE, DK, FR, NL, NO, SE, UK). Columns (6) and (7) show the results of estimating the event study regression $\Delta CDS_{i,T+l} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,k,T+l} + \epsilon_i$ separately for the early (2014M10-2016M07) and late (2016M12-2018M11) part of our sample. All regression are estimated on the balanced sample where both a CDS and a equity price are available for every bank. The regression is estimated for six event points: October 26, 2014; November 25, 2015; July 29, 2016; December 2, 2016; November 24, 2017; and November 2, 2018. The Δ is taken between 3 days after ($l = 3$) and one day before the data release. Panel B repeats the exercise with the growth rate of equity prices on the LHS. P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 1.5: Event study results – sector x bank nationality splits

Panel A – sector x bank Nationality split for CDS

	(1) ΔCDS Core	(2) ΔCDS Periphery	(3) ΔCDS Core	(4) ΔCDS Periphery	(5) ΔCDS Core	(6) ΔCDS Periphery
$\Delta\widehat{SEL}_{i,Sovereign,t}$	-2.39	0.54***				
	(0.23)	(0.00)				
$\Delta\widehat{SEL}_{i,Bank,t}$			2.20**	0.64		
			(0.01)	(0.68)		
$\Delta\widehat{SEL}_{i,NBPS,t}$					0.78***	-0.32
					(0.00)	(0.48)
Constant	-0.05***	-0.04***	-0.05***	-0.03*	-0.06***	-0.03*
	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)
R^2	0.02	0.20	0.04	0.00	0.04	0.01
N	100	72	100	72	100	72

Panel B – sector x bank nationality split for stocks

	(1) ΔEquity Core	(2) ΔEquity Periphery	(3) ΔEquity Core	(4) ΔEquity Periphery	(5) ΔEquity Core	(6) ΔEquity Periphery
$\Delta\widehat{SEL}_{i,Sovereign,t}$	0.37	-0.36***				
	(0.40)	(0.00)				
$\Delta\widehat{SEL}_{i,Bank,t}$			-0.04	0.75		
			(0.91)	(0.59)		
$\Delta\widehat{SEL}_{i,NBPS,t}$					-0.21**	0.13
					(0.01)	(0.72)
Constant	0.03***	0.02**	0.03***	0.01	0.03***	0.01
	(0.00)	(0.02)	(0.00)	(0.15)	(0.00)	(0.15)
R^2	0.00	0.18	0.00	0.01	0.03	0.00
N	100	72	100	72	100	72

Note: Panel A shows the results of estimating the event study regression $\Delta CDS_{i,T+l} = \alpha + \beta \cdot \Delta\widehat{SEL}_{i,k,T+l} + \epsilon_i$. separately for banks from the European periphery (ES, HU, IE, IT, PT) and the European core (AT, BE, DE, DK, FR, NL, NO, SE, UK) on the balanced sample where both a CDS and a equity price are available for every bank. The regression is estimated for six event points: October 26, 2014; November 25, 2015; July 29, 2016; December 2, 2016; November 24, 2017; and November 2, 2018. The Δ is taken between 3 days after ($l = 3$) and one day before the data release. Panel B repeats the exercise with the growth rate of equity prices on the LHS. P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Next, we dig deeper into understanding the importance of the above dimensions by examining the combination of the splits between counterparty sector and bank nationality (Table 1.5). The CDS spread and equity prices of periphery banks reacted strongly to updates about their expected losses vis-a-vis the sovereign sector, but not vis-a-vis the other two sectors. By contrast, core banks exhibit almost the exact opposite pattern. More concretely, updates about sovereign sector expected losses did not have a significant impact on core banks' asset prices. Conversely, the CDS spreads and equity prices of core banks reacted significantly to updates about expected losses vis-a-vis the non-bank private sector. Furthermore, core banks' CDS spreads were also significantly affected by updates in the expected losses on their interbank exposures.

Why were asset markets most sensitive to new information about periphery banks' sovereign risk exposure and core banks' non-bank private sector and interbank exposures? The bank-sovereign loop was a major concern in the European periphery, especially in the early part of our sample (Acharya et al. [2014], Altavilla et al. [2017], Bocola [2016]; others). One of its main channels went through periphery banks' exposures to their domestic sovereigns. Thus, it was natural for CDS and equity markets to be very sensitive to any new information about exactly those exposures. While core banks also had sizeable sovereign exposures, the majority of them were to their respective domestic governments, whose default risk was much lower than that of periphery governments. Consequently, the impact of news about their sovereign portfolios on CDS spreads and equity prices was not nearly as large as in the case of periphery banks. Meanwhile, the exposures of core banks to the non-bank private sector and to other banks have traditionally been more complex and spread across a much wider set of countries and industries than those of periphery banks. As a result, the marginal impact of new information about those sets of exposures was considerably larger for core banks than for periphery banks. Finally, the result that new information on interbank exposures had a significant impact on core banks' CDS spreads but not on their equity prices is consistent with Hypothesis 2c and with the intuition behind it. In the case of equity prices, the negative impact of an increase in the riskiness of a bank's lending portfolio on its expected losses tends to be (at least partially) offset by the positive impact of the higher returns associated with riskier lending. By contrast, in the case of CDS spreads, the offsetting effect of the higher returns tends to be negligible since positive news about a bank's profitability affect CDS spreads only to the extent that they reduce the probability of the bank becoming insolvent.

1.4 Implications of bank opacity

1.4.1 Impact of bank opacity on bank funding

In this section, we examine the implications of bank opacity for bank funding interest rates and volumes. More specifically we focus on funding from US MMFs, which are a major source of funding for large European banks (Ivashina et al. [2015]). These large institutions should be more likely to perform a high level of due diligence when lending to banks (e.g. by gathering additional information about banks' exposures and expected losses) than other, less sophisticated investors (e.g. retail depositors). Hence, MMFs may be able to charge banks a funding rate that takes into account banks' actual expected loss levels more accurately than CDS spreads or equity prices do. To examine this hypothesis, we use the iMoney database of monthly holdings of US MMFs. The database contains information about the quantities (volumes) and prices (interest rates) of US MMFs' lending to the banks in our sample. We aggregate these data to a semi-annual frequency. Unfortunately, this data is only available for five periods of our sample (2012H2 to 2014H2).

We first examine whether the interest rates that US MMFs charged European banks reflected the gap between banks' actual expected losses and those estimated based on publicly available information ($EL\_Gap_{i,t-1}$) by running the following regression:

$$\begin{aligned} Interest\_rate_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \\ \gamma' X_{i,t-1} + BankFE + FundFE + TimeFE + \epsilon_{i,t}, \end{aligned} \tag{1.11}$$

where $Interest\_rate_{i,j,t}$ is the volume-weighted average interest rate paid by bank i to MMF j at time t, $X_{i,t-1}$ is a vector that contains lagged values of total assets, the Tier 1 capitalization level, return on assets, loan loss reserves over total loans, the CDS spread and the net interest margin.

If MMFs had more information about bank portfolios than other market participants, the estimated coefficient (β) on the expected loss gap variable would be positive. Intuitively, if an MMF has additional (non-public) information that the expected loss of a given bank is higher than what is publicly known (i.e. that $EL\_Gap_{i,t-1} > 0$), then it would charge that bank a higher interest rate than the one implied by its CDS spread. Hence, the funding rate on the LHS of our regression should be positively associated to the $EL\_Gap_{i,t-1}$ levels on the RHS after controlling for the level of the actual CDS spread (and other bank-level characteristics). Furthermore, we also investigate whether MMF funding volumes were affected by the gap between actual and market-estimated expected losses by replacing the interest rate variable on the left-hand side of Equation 1.11 with several variables capturing MMF funding volumes:

$$Fund\_vol_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \gamma' X_{i,t-1} + BankFE + FundFE + TimeFE + \epsilon_{i,t}, \tag{1.12}$$

where $Fund\_vol_{i,j,t}$ stands for the following set of variables measuring the funding provided to bank i by MMF j: (i) the outstanding stock of MMF funding at time t, (ii) the change in the outstanding stock between t and $t-1$, (iii) the growth rate of the outstanding stock between t and $t-1$ and (iv) the change in the outstanding stock between t and $t-1$, scaled by total assets at $t-1$.

Panel A of Table 1.6 presents the results from the above regressions. Column (1) reveals that there is no statistically significant relationship between the expected loss gap and the interest paid by banks to MMFs. Hence, MMFs do *not* correct the mispricing of CDS spreads documented in Section 1.3.3 and this mispricing also feeds through to banks' MMF-related funding costs. This implies that banks' borrowing costs are distorted by asymmetric information even when the funding is provided by sophisticated investors, which are supposed to be more informed and, consequently, least affected by bank opacity.

If, as documented above, bank funding rates are not reflecting the true risk in their portfolios, it is reasonable to assume that banks obtain more or less funding depending on whether the conditions they face are favorable or not. The results reported in columns (2) to (5) confirm this hypothesis. Regardless of the measure used to quantify funding amounts, banks whose funding conditions are favorable because markets are underestimating their expected losses (i.e. $EL\_Gap_{i,t} > 0$) obtain significantly more MMF funding. The estimates are not only statistically significant, but also economically meaningful. For example, the coefficient reported in column (5) implies that for each percentage point with which the market is underestimating their expected losses, banks increase their MMF funding by 0.5% of their total assets.

Table 1.6: Money Market Mutual Fund (MMF) financing

Panel A – standard fixed-effects					
	(1) Interest paid	(2) Funding Stock	(3) Funding Flow	(4) Funding Growth	(5) Scaled Funding Flow
$EL\_Gap_{i,t-1}$	0.13	609.26**	685.77***	3.24**	0.52***
	(0.40)	(0.01)	(0.00)	(0.02)	(0.00)
R^2	0.45	0.62	0.16	0.20	0.17
N	722	722	670	670	670
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes

Panel B – Khwaja and Mian [2008] fixed-effects					
	(1) Interest paid	(2) Funding Stock	(3) Funding Flow	(4) Funding Growth	(5) Scaled Funding Flow
$EL\_Gap_{i,t-1}$	-0.01	647.47*	738.56***	3.34**	0.56***
	(0.93)	(0.05)	(0.00)	(0.03)	(0.00)
R^2	0.49	0.65	0.25	0.31	0.28
N	722	722	670	670	670
Fund x Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes

Note: Panel A shows the results of estimating the equations $Y_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \gamma' X_{i,t-1} + BankFE + FundFE + TimeFE + \epsilon_{i,t}$ where Y is either the volume-weighted average interest rate paid by banks or one of the following funding volume measures: (i) the outstanding stock of MMF funding, (ii) the change in the outstanding stock, (iii) the growth rate of the outstanding stock or (iv) the change in the outstanding stock scaled by lagged total assets. Panel B repeats the exercise with bank and MMF $\times$ time fixed effects. P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. R^2 is within R^2. Data is available for 15 banks and 58 MMFs between 2012Q4 and 2014Q4.

Are the above results driven by supply factors (related to the lending MMFs) or demand factors (related to the borrowing banks)? To investigate this question empirically, we follow Khwaja and Mian [2008] and re-estimate the specifications in Equation 1.11 and 1.12 while including (MMF) Fund x Time fixed effects. This allows us to control for the supply of funding by MMFs, as many MMFs lend to several banks in our sample at the same time. The results from these alternative specifications are presented in Panel B of Table 1.6. The coefficients in all columns are very close (in terms of both, magnitude and significance) to their counterparts in Panel A of Table 1.6. This suggests that the equilibrium outcome of a higher MMF funding inflow is driven primarily by demand factors.

In order to understand the intuition behind the above set of results, consider the following example. Suppose that there are two banks with identical expected loss values - Bank A, whose expected losses are accurately assessed by the market (i.e. $EL\_Gap_{i,t} = 0$), and Bank B, whose expected losses are underestimated by the market (i.e. $EL\_Gap_{i,t} > 0$). All else the same, Bank B's demand curve would be to the right of Bank B's demand curve since for any interest rate level, it would be optimal for Bank B to borrow more in order to take advantage of the funding costs that are more favorable than the ones implied by the actual (as opposed to the market-estimated) level of its expected losses. Since, as documented in column (1) of Table 1.6, the interest rates on banks' MMF funding do not depend on the gap between banks' actual and market-estimated expected losses, the two banks would face (de-facto) the same supply curve. As a result, the two banks would end up paying the same interest rate, while the bank whose expected losses are underestimated by markets would end up borrowing more from MMF. This is illustrated in Figure 1.2.[16]

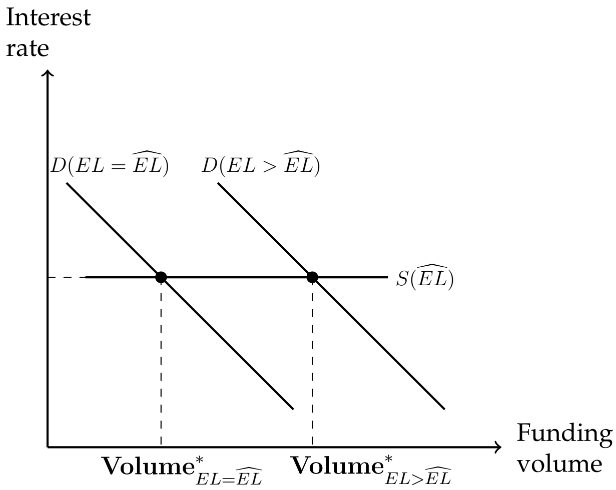
1.4.2 How is bank opacity linked to asset composition and performance?

Next, we investigate the effects of asymmetric information on bank credit supply. We do that by using syndicated loan data from the Dealscan database.[17] We construct a loan-level dataset by first matching banks with borrowers and then matching borrowers to their balance sheet information (obtained from the Amadeus database). Since many

[16] The supply curve is depicted as flat for the ease of exposition. The demand curve(s) need to be steeper than the supply curve for our intuition to hold.

[17] Appendix 1.A.2 lists details on the preparation of the raw data.

Figure 1.2: Wholesale funding market - a stylized illustration



Note: This figure displays a stylized illustration of the bank wholesale funding market. $S(\cdot)$ represents the supply of wholesale funding by MMFs (as a function of banks' estimated expected losses) and $D(\cdot)$ represents the demand for wholesale funding by banks (as a function of the gap between their actual expected losses and their estimated expected losses). EL stands for $EL_{i,t}$ and $\widehat{EL}$ stands for $\widehat{EL}_{i,t}$ as defined in Section 1.2.1.

firms borrow from more than one bank, we can use the identification strategy of Khwaja and Mian [2008] to disentangle credit supply and demand:

$$\begin{aligned} Loan\_growth_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \theta \cdot EL\_Gap_{i,t-1} \times FirmType_j + \\ \gamma' X_{i,t-1} + BankFE + Borrower \times TimeFE + \epsilon_{i,t}, \end{aligned} \tag{1.13}$$

where $Loan\_growth_{i,j,t}$ describes the growth rate of the outstanding stock of loans extended by bank i to borrower j at time t; $Borrower \times TimeFE$ control for credit demand. Following Davis and Haltiwanger [1992] and Peydró et al. [2021], we define the loan growth rate as $100 \frac{Loan\_Volume_{i,j,t} - Loan\_Volume_{i,j,t-1}}{\frac{1}{2}(Loan\_Volume_{i,j,t} + Loan\_Volume_{i,j,t-1})}$. This variable lies in the closed interval $[-200, 200]$ and allows us to measure growth rates for new loans even in cases in which the previous period volume was zero. $FirmType_j$ captures potential interaction terms in the regression framework which we describe in more detail below.

The results from the estimation of Equation 4.7 are presented in column (1a) of Panel A in Table 1.7. There appears to be no statistically significant relationship between the level of bank opacity and credit supply decision. Are we taking out too much variation using the rich fixed-effects structure? Column (1b) tries to answer this question by replacing the borrower x time fixed effects with separate borrower and time fixed effects. The estimate of the coefficient on the expected loss gap variable remains insignificant. Thus, the level of bank opacity does not appear to be linked to the quantity of loans they extend to the real sector.

While bank opacity may not be linked to overall bank loan volumes, it is possible that it is linked to the composition of borrowers. In order to test this hypothesis, we first interact $EL\_Gap_{i,t-1}$ with a dummy variable ($High\_Risk_{j,2012}$) indicating a low credit rating (BB or worse) of the respective borrower in 2012. We use the 2012 credit rating to ensure that there is no endogeneity in the borrower risk classification. The results (presented in column (2)) do not reveal a significant relationship.

Since lending to low-rated borrowers is typically associated with higher regulatory capital charges, banks might be less willing to lend to such borrowers when searching for yield. Instead, they might try to lend to the highest yielding borrowers within the same credit rating category. To measure this, we follow the approach by Acharya et al. [2021], and measure the gap between the interest rate paid by the each borrower and the average interest rate paid by other borrowers in the same industry-country combination who have the same credit rating. A positive gap reveals that a given borrower is willing to pay a higher interest rate than its peers with identical ratings. This can indicate underlying risk that is not (yet) captured by the credit rating and therefore allows banks to search for yield without having to incur higher capital charges. The result for interacting this interest gap variable ($Interest\_Gap_{j,2012}$) – again measured in 2012 – with $EL\_Gap_{i,t-1}$ can be found in column (3). Once again, the estimated coefficient on the key interaction term is not statistically significant.

Are these aggregate results masking any heterogeneity across bank nationalities? As documented in Acharya et al. [2018] or De Marco [2019], banks from the European periphery often suffered from low capital levels, high non-performing loan shares, and low profitability in general. Thus, their incentives to search for yield were much stronger than those of their peers from core European countries. Panels B and C in Table 1.7 report the results obtained when re-estimating the previous set of regressions while splitting our sample of banks into two country groups - "core" and "periphery" (as defined in the previous section). Panel B reveals that the results for core banks do not differ qualitatively from those estimated on the full sample. However, the results for periphery banks (displayed in Panel C) are considerably different. The estimated coefficients on the interaction terms of the expected loss gap with both, the high-risk dummy

Table 1.7: Loans to the non-bank private sector

	(1a)	(1b)	(2)	(3)
Panel A – all banks				
$EL\_Gap_{i,t-1}$	11.73	19.01	285.27	203.19
	(0.89)	(0.45)	(0.20)	(0.16)
$EL\_Gap_{i,t-1} \times High\_Risk_{j,2012}$			-16.47	
			(0.96)	
$EL\_Gap_{i,t-1} \times Interest\_Gap_{j,2012}$				5783.58
				(0.68)
R^2	0.62	0.29	0.60	0.59
N	15011	15011	1963	2939
Panel B – core banks				
$EL\_Gap_{i,t-1}$	23.40	12.35	-369.91	-292.95
	(0.84)	(0.78)	(0.34)	(0.51)
$EL\_Gap_{i,t-1} \times High\_Risk_{j,2012}$			544.13	
			(0.67)	
$EL\_Gap_{i,t-1} \times Interest\_Gap_{j,2012}$				28366.10
				(0.59)
R^2	0.65	0.30	0.69	0.63
N	10677	10677	1070	1631
Panel C – periphery banks				
$EL\_Gap_{i,t-1}$	-10.82	-5.86	293.57	640.88*
	(0.94)	(0.91)	(0.26)	(0.07)
$EL\_Gap_{i,t-1} \times High\_Risk_{j,2012}$			1726.47***	
			(0.00)	
$EL\_Gap_{i,t-1} \times Interest\_Gap_{j,2012}$				41808.49**
				(0.03)
R^2	0.71	0.30	0.65	0.67
N	4334	4334	893	1208
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	No
Borrower FE	No	Yes	No	No
Borrower × Time FE	Yes	No	Yes	Yes

Note: Panel A shows the results of estimating the equations $Loan\_growth_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} \times Y_j + \gamma' X_{i,t-1} + BankFE + Borrower \times TimeFE + \epsilon_{i,t}$ where Y is either 1, an indicator for high borrower risk ($High\_Risk_{j,2012}$) or a variable measuring the search-for-yield intensity of the loan ($Interest\_Gap_{j,2012}$). Panel B repeats the exercise for the sub-sample of banks from the European core (AT, BE, DE, DK, FR, NL, NO, SE, UK). Panel C repeats the exercise for the sub-sample of banks from the European periphery (ES, HU, IE, IT, PT). P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. R^2 is within R^2. Data is available for 520 borrowing firms and 41 banks.

(in column (2)) and the search-for-yield dummy (in column (3)) are statistically significant. This suggests that periphery banks whose credit risk was understated by markets not only received more wholesale funding (as documented in Section 1.4.1), but also used that funding (at least partially) to chase yield by making more high-yielding loans to riskier borrowers.[18]

The above results naturally raise two follow-up questions. First, did the search-for-yield of periphery banks whose expected losses were underestimated by markets result in higher profitability (at least in the short-run)? If those banks received funding at rates that were lower than those implied by their (actual) expected losses (as documented in Section 4.1), but were more likely to lend to higher-risk borrowers at (relatively) higher interest rates (as documented in Table 1.7), then their net interest margins should have increased. Second, if core banks whose expected losses were underestimated by markets were not searching-for-yield (as implied by the results in Table 1.7), what were they doing with the additional wholesale funding they received (documented in Section 4.1)? We shed light on both questions by estimating the following regression specification:

$$\Delta Y_{i,t+h} = \beta \cdot EL\_Gap_{i,t} + \gamma' X_{i,t} + BankFE + TimeFE + \epsilon_{i,t+h}, \tag{1.14}$$

where the LHS variable ($\Delta Y_{i,t+h}$) is either the growth rate of total loans, the growth rate of debt securities or the change in the net interest margin of bank i between periods t and $t+h$. We estimate the above regressions for values of h between one and three, thus analyzing the respective relationships over a horizon of one-and-a-half years (since, as mentioned above the data used in this exercises are semi-annual). Loans and debt securities make up almost all of banks' interest-bearing assets. The (total) loan regressions allow us to test for the existence of potential links between banks' overall loan volumes and asymmetric information. [19] Debt securities are the natural alternative investment venue for banks, if loan market adjustments are not perceived as optimal, e.g. because of

[18]The Khwaja and Mian [2008] approach relies on having a sample in which firms borrow from multiple banks. In Europe, where (i) the syndicated loan market accounts for a relatively smaller share of the overall loan market and (ii) firms tend to have fewer bank relationships, this approach is less likely to leave enough variation for the identification of statistically significant effects. Therefore, the fact that we find statistically significant effects for periphery banks can be interpreted as particularly strong evidence, as it emerges from a specification that is stacking the odds against it. The approach has also been applied to a European setting in several cases (e.g. Acharya et al. [2021], Acharya et al. [2018]).

[19]It is important to note that the "total loan" category that we examine in this exercise is (by definition) considerably broader than the variable used in Table 1.7), which covers syndicated loans to the non-bank private sector.

unfavorable demand conditions. Lastly, the net interest margin captures the difference in earned interest and paid interest and is a central metric for profitability of banks.

Table 1.8 summarizes the results. Panel A first shows the results for all banks, before Panel B and C split the sample along the (previously defined) core/periphery bank nationality dimension. Panel A documents that banks whose expected losses are underestimated by markets tend to have higher net interest margins (over all horizons we examine) and greater holdings of debt securities holdings (after 1.5 years). The relationship between bank opacity and total loan growth is not statistically significant.

Panel B reveals that the debt securities increase is driven by core banks. Meanwhile, the net interest margins of core banks are not significantly linked to their opacity levels. Conversely, Panel C documents that the net interest margins increase in the overall sample is driven by periphery banks. In turn, the relationship between the debt securities holdings of periphery banks their opacity levels is not statistically significantly.

In sum, the above results suggest the following answers to the two questions we examined in this last set of regressions. First, periphery banks whose expected losses were underestimated by markets increased their net interest margin by searching for yield. Second, core banks whose actual expected losses were greater than markets' estimates used the additional wholesale funding they obtained to expand their debt securities holdings, but saw no increase in their net interest margins.

Table 1.8: Asset composition and performance

	$\Delta L_{i,t+1}$	$\Delta L_{i,t+2}$	$\Delta L_{i,t+3}$	$\Delta DS_{i,t+1}$	$\Delta DS_{i,t+2}$	$\Delta DS_{i,t+3}$	$\Delta NIM_{i,t+1}$	$\Delta NIM_{i,t+2}$	$\Delta NIM_{i,t+3}$
Panel A – all banks									
$EL\_Gap_{i,t}$	0.03	-0.05	-0.13	0.01	0.37	0.82***	0.30**	0.64**	0.79**
	(0.53)	(0.64)	(0.38)	(0.92)	(0.13)	(0.00)	(0.03)	(0.02)	(0.02)
R^2	0.15	0.15	0.12	0.05	0.13	0.19	0.14	0.16	0.18
N	331	292	254	321	285	245	327	288	248
Panel B – core banks									
$EL\_Gap_{i,t}$	0.01	-0.13	-0.31	0.19	0.62*	0.99**	-0.08	0.16	-0.05
	(0.85)	(0.39)	(0.18)	(0.33)	(0.07)	(0.03)	(0.60)	(0.61)	(0.91)
R^2	0.24	0.25	0.23	0.12	0.20	0.23	0.12	0.09	0.07
N	216	189	164	206	179	154	210	182	157
Panel C – periphery banks									
$EL\_Gap_{i,t}$	0.05	0.05	-0.02	-0.09	0.23	0.75	0.49**	1.06**	1.20**
	(0.55)	(0.77)	(0.93)	(0.67)	(0.57)	(0.10)	(0.05)	(0.02)	(0.02)
R^2	0.15	0.12	0.10	0.10	0.15	0.24	0.31	0.35	0.44
N	115	103	90	115	106	91	117	106	91
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Panel A shows the results of estimating the equations $\Delta Y_{i,t+h} = \beta \cdot EL\_Gap_{i,t} + \gamma' X_{i,t} + BankFE + TimeFE + \epsilon_{i,t+h}$ where Y is either the growth in loans ($\Delta L_{i,t+h}$), the growth in debt securities ($\Delta D_{i,t+h}$) or the change in the net interest margin ($\Delta NIM_{i,t+h}$) with h varying from 1 to 3. Panel B repeats the exercise for the sub-sample of banks from the European core (AT, BE, DE, DK, FR, NL, NO, SE, UK). Panel C repeats the exercise for the sub-sample of banks from the European periphery (ES, HU, IE, IT, PT). P-values based on bank-clustered standard errors in parenthesis. All variables are winsorized at the 1% and 99% level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. R^2 is within R^2.

1.5 Conclusion

We examine the patterns and implications of bank opacity in Europe by using a detailed bank-level dataset on the geographical and sectors distribution of the exposures of 130 European banks between 2012 to 2018. We first document that public information releases by the EBA had a significant impact on banks' CDS spreads and equity prices, which implies that market participants were imperfectly informed about banks' credit risk levels. We also show that there was considerable heterogeneity across bank nationalities and counterparty sectors - markets reacted most strongly to new information about the sovereign sector exposures of banks from the European periphery and the non-bank private sector exposures of banks from the European core.

Furthermore, we show that banks whose credit risk was underestimated by markets benefited from favorable wholesale funding rates and used this to secure additional funding. This additional funding was invested in riskier and higher-yielding loans by banks from the European periphery and in debt securities by banks from the European core. While the above strategy of periphery banks increased their net interest margins in the short-run, it can have adverse consequences for the real economy in the long run as theoretically stipulated by Martinez-Miera and Repullo [2017].

Our work presents several possible directions for future research. First, it would be important to examine the generality of our main results by investigating the degree to which they are also present in other geographic regions and time periods. Second, it would be interesting to use the directional bank opacity measure that we introduce in other empirical settings and examine its links with more conventional measures of bank opacity and asymmetric information. Finally, it would be intriguing to apply the novel event study methodology that we employ in this paper in order to quantify the impact of the public releases of other datasets containing information on the distribution of bank exposures.

Appendix

1.A Additional information on the data used in the empirical analysis

1.A.1 Using the BIS IBS to impute missing EBA data

Since the EBA solely provides detailed information on the top 10 countries, only about 70% of the total exposures can be broken down by country and sector. Moreover, since the top 10 countries are selected by total exposure, for some banks and sectors as little as 25% of the exposures might be covered.[20] To overcome this problem of missing data, we use the CBS data set provided by the BIS. The CBS contains information on the outstanding exposure of country-level banking systems to three main sectors (*Sovereign*, *Banks*, *NBPS*) in more than 200 countries. We then follow the following imputation scheme:
Let $CBS_{c,j,k,t}$ be the exposure of the banking system in country c to sector k in counterparty country j at time t. We impute the exposure values which are not broken down by the EBA using exposure shares calculated from the CBS numbers in the following way: 1) from all available $CBS_{c,j,k,t}$ combinations delete the ones that are provided by the EBA for the bank at hand; 2) calculate the sum of non-allocated exposures in the CBS data set by summing over all remaining $CBS_{c,j,k,t}$ combinations for a given t; 3) calculate exposure shares by dividing each single $CBS_{c,j,k,t}$ by the sum computed in step 2); 4) compute the non-allocated exposure in the EBA data set by subtracting the sum over the exposures vis-a-vis the top 10 countries from the overall exposure sum; 5) apply

[20] Think about a bank who has 90 units of private sector exposure evenly spread across 10 countries, including the home country, and 10 units of public sector exposure of which 2 units are domestic and the remainder is evenly spread across two countries which are not part of the 10 countries in the private sector. Then, from the public sector exposure, the data set will only attribute the 2 domestic units (i.e. 20%) to a country and will be silent about the counterparty countries of the remaining public exposure, because they make up too little of the overall exposure.

the shares calculated in step 3) to the non-allocated sum from step 4) to obtain imputed exposures for every bank vis-a-vis each of the three sectors in all available countries for every t. In less precise words, for all the exposures not provided by the EBA, we assume constant shares of exposures across banks in one country; e.g. bank 1 and 2, both from France, are supposed to have the same share x of their non-allocated exposure vis-a-vis the banking sector in Sweden.

1.A.2 Preparation of Dealscan data

We obtain loan-level data from the Thomson Reuters LPC DealScan database, which provides detailed information on European syndicated loans including information on lenders as well as loan contract terms. For banks to be included in the sample, we follow the previous literature (e.g. Ivashina [2009]; Heider et al. [2019]) and require that banks must serve as lead arranger in the syndicate.[21] If the loan allocation between syndicate members is unknown, we divide the loan facility equally among syndicate members. Also following the previous literature (e.g. Acharya et al. [2018]), we transform the data and calculate the semi-annual outstanding exposure of bank i to non-financial firm j, using the maturity information on each loan.

We match DealScan borrowers in our sample to firms in the Amadeus database. The final loan-level sample comprises 41 banks that arrange loans to 520 non-financial firms.

[21] Following Ivashina [2009], a bank is classified as lead arranger if it has any one of the following lender roles in DealScan: administrative agent, bookrunner, lead arranger, lead bank, lead manager, agent or arranger.

1.A.3 List of banks in data set

Table 1.A.1: List of banks in sample

Name	Country	CDS data (1/0)	Equity data (1/0)
ABN AMRO Group N.V.	NL	1	0
Banca Monte dei Paschi di Siena SpA	IT	1	1
Banco Bilbao Vizcaya Argentaria, SA	ES	1	1
Banco BPI SA	PT	1	1
Banco Comercial Portugues SA	PT	1	1
Banco de Sabadell, SA	ES	1	1
Banco Popular Español SA	ES	1	0
Banco Santander SA	ES	1	1
Bayerische Landesbank	DE	1	0
BNP Paribas SA	FR	1	1
Caixa Geral de Depositos SA	PT	1	0
Cooperatieve Rabobank U.A.	NL	1	0
Commerzbank AG	DE	1	1
Danske Bank	DK	1	1
DEPFA BANK Plc	IE	1	0
Deutsche Bank AG	DE	1	1
Deutsche Pfandbriefbank AG	DE	1	0
Deutsche Zentral-Genossenschaftsbank AG	DE	1	0
Dexia NV	BE	1	1
DNB Bank ASA	NO	1	1
Erste Group Bank AG	AT	1	1
HSBC Holdings Plc	UK	1	1
HSH Nordbank AG	DE	1	0
Intesa Sanpaolo SpA	IT	1	1
Jyske Bank	DK	1	1
KBC Group NV	BE	1	1
Landesbank Baden-Wuerttemberg	DE	1	0
Landesbank Hessen-Thueringen Girozentrale	DE	1	0
Landwirtschaftliche Rentenbank	DE	1	0
Lloyds Banking Group Plc	UK	1	1
Mediobanca - Banca di Credito Finanziario SpA	IT	1	1
N.V. Bank Nederlandse Gemeenten	NL	1	0
Norddeutsche Landesbank Girozentrale	DE	1	0
Novo Banco	PT	1	0
OTP Bank Nyrt.	HU	1	1
Permanent TSB Group Holdings Plc	IE	1	1
Raiffeisen Bank International AG	AT	1	1
RCI banque (Renault Credit International)	FR	1	0
Skandinaviska Enskilda Banken - group	SE	1	1
Societe Generale SA	FR	1	1
Standard Chartered Plc	UK	1	1
Svenska Handelsbanken - group	SE	1	1
Swedbank - group	SE	1	1
The Governor and Company of the Bank of Ireland	IE	1	1
The Royal Bank of Scotland Group PLC	UK	1	1
UniCredit SpA	IT	1	1
Unione di Banche Italiane SCpA	IT	1	1
VW Financial Services AG	DE	1	0

1.B Supplementary theoretical proofs and derivations

In the following we briefly derive the bank debt claim pricing formula used in the main text based on CARA utility and normally distributed beliefs about bank default.

Assume that the utility of an investor from payoff p_1 and price p_0 is given by

$$U(P) = -e^{-\lambda(p_1-p_0)},\ \lambda > 0. \tag{1.15}$$

This exponential utility function fulfils the Arrow-Pratt definition of absolute constant risk aversion with risk aversion coefficient λ. Since p_1 is assumed to be normally distributed with mean μ and variance σ^2, the expected utility of investing in the project is given by

$$\begin{aligned} E(U(p_1)) =& \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} -e^{-\lambda(p_1-p_0)} e^{-\frac{(p_1-\mu)^2}{2\sigma^2}} dp_1 \\ =& \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} -e^{-(\lambda(p_1-p_0)+\frac{(p_1-\mu)^2}{2\sigma^2})} dp_1. \end{aligned} \tag{1.16}$$

Next, we regroup terms using the binomial theorem to pull out of the integral all the terms independent of the realization of P:

$$E(U(p_1)) = -\frac{e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2}-p_0)}}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(\frac{(p_1-\mu+\lambda\sigma^2)^2}{2\sigma^2})} dp_1. \tag{1.17}$$

If we now define $\hat{\mu} = \mu - \lambda\sigma^2$, we have

$$E(U(p_1)) = -e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2}-p_0)} \cdot \underbrace{\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(p_1-\hat{\mu})^2)}{2\sigma^2}} dp_1}_{=1}, \tag{1.18}$$

where the second term is just the area under the normal density function for a variable with mean $\hat{\mu}$ and variance σ^2. This leaves us with the following expression for the expected utility:

$$E(U(p_1)) = -e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2}-p_0)}, \tag{1.19}$$

which means that investors are trying to maximize $\mu - \frac{\lambda\sigma^2}{2} - p_0$. Further assume that the investor always faces the outside option of investing in the risk-free asset which yields the safe net return $r_f = 0$ and reservation utility -1. The project managers want to minimize the price p_0 they have to pay for one share. Hence, the equilibrium price p_0^* is equal to $\mu - \frac{\lambda\sigma^2}{2}$. Any price p_0 higher than p_0^* will make the investor choose the risk-free asset. Any price p_0 lower than p_0^* will not be accepted by the bank as she knows that the investor is willing to pay more. Since μ is $1 - \overline{PD}$ in our setting, the price becomes $(1 - \overline{PD}) - \frac{\lambda}{2}\sigma^2$.

Chapter 2

The Janus face of bank geographic complexity

Joint with Iñaki Aldasoro and Bryan Hardy (both Bank For International Settlements).

2.1 Introduction

Global banks' complexity is a major concern for policy makers, as shown by its prominence within the framework to regulate global systemically important banks (GSIBs). Complexity, however, is not a clearly defined concept and can take different forms. It could arise from the size and diversity of a bank's loan portfolio (Doerr and Schaz [2020]), it could be related to the extent and nature of investment activities (BCBS [2013]), or it could be determined by the organizational and geographic structure of the bank (Cetorelli and Goldberg [2016, 2014]). This paper focuses on the geographic structure of international banking affiliates (geographic complexity) and examines how it helps banks to cope with the two main factors governing their business: the economic and regulatory environments.

Geographic complexity can affect bank risk in opposite directions. On one hand, it can provide diversification value to financial institutions and can thus be beneficial for bank risk and financial stability. We document that a higher degree of geographic complexity in the bank's affiliate network helps banks dampen the adverse impact of local economic shocks (i.e. in the country of headquarters) on their riskiness.

On the other hand, geographic complexity can also increase risk by changing the way regulation impacts the bank. Tighter prudential regulation is associated with higher capitalization levels. However, we show that when there is higher geographic complexity, the increase in the risk-based capital ratio (regulatory Tier 1 capital) is smaller following a tightening of prudential regulation. This implies that a wider geographic reach can provide banks with a broad range of ways to respond to the regulation, potentially impacting their resilience and risk.

Bank geographic complexity therefore has a Janus face. On the one hand, it helps mitigate the impact of local economic shocks and hence strengthens banks' resilience. On the other hand, it can also pose a risk by giving bank prudential regulation a looser grip.

To perform our analysis, we build a new, unique bank-level dataset on geographic complexity using the BIS Banking List (see Section 3.3 for more details). Based on this list of internationally active banking entities, we obtain a dataset comprising 96 of the largest bank holding companies (BHCs)[1] in the world, including most of the sample used by the Basel Committee on Banking Supervision (BCBS) in the GSIB assessment exercise. The data are unique in that they provide a large, global sample of the most relevant international BHCs in a cross-country panel. We match these data with balance sheet information at the BHC level, as well as macro indicators and information about the regulatory environment at the country level. This allows us to test how bank geographic complexity relates to measures of bank health and risk and their main driving forces. We exploit the cross-country nature of the dataset to control for various confounding factors, including via country-time fixed effects, and obtain results that hold across different country settings.

We compute a Herfindahl-Hirschman (HHI) based measure of geographic representation and complexity at the BHC-year level. This measure conceptually accounts for the bank's number of international banking affiliates, its geographic reach (number of host countries with affiliates) and the concentration of affiliates across its host countries. We interpret the HHI as a measure of geographic complexity and diversification, but not business model complexity/diversification. Complexity and diversification need in principle not coincide. A large domestically oriented financial institution can have a very complex business model, whereas a bank with a wider international footprint might be simpler in terms of business model diversity. [2] We document that our mea-

[1]Throughout we use bank, BHC and banking group interchangeably. Our unit of analysis is always the BHC.

[2]The first type of financial institutions will not be part of our dataset by construction, as *only* internationally active banking entities report to the BIS international banking statistics. But even if such a bank would

sure of geographic complexity contains information complementary to that captured by the size (total assets) of the bank, the BCBS's measures of complexity and cross-jurisdictional activity from the GSIB assessment exercise, as well as the geographic complexity of the syndicated loan portfolio.[3]

Our analysis is split into two sections. The first focuses on the role of geographic complexity in affecting the relation between bank risk and economic shocks in the country of the BHC's headquarters. The second section investigates the relevance of geographic complexity for the impact of country prudential regulation (home country, host countries, or both) on BHC's risk. We use different measures of risk for the different parts of our analysis. When looking at local economic shocks, we focus on the z-score. This measure is the most comprehensive and commonly used measure of realized risk. It better reflects changes to risk due to the changing economic environment. When examining the effects of regulation, we focus instead on risk-based capitalization, as this is a key target of regulators that proxies an ex-ante perspective to bank risk.

We document that negative shocks to the growth of real GDP in the home country (i.e. local shocks) drive up bank risk.[4] The more geographically diversified a bank is, however, the more it can cushion this increase in risk. The diversification benefit afforded by geographic complexity depends on three key factors: the organizational structure, the business model, and the host location characteristics.

First, the organizational structure through which a bank decides to be present abroad (i.e. branches versus subsidiaries) can be an important determinant of the ability to smooth shocks. Subsidiaries are locally chartered (i.e. in host jurisdictions), are separately capitalized and are regulated by host entities. They therefore operate more independently, and so make it more difficult for a BHC to adjust business across their affiliates in response to shocks. In line with this, we find that operating abroad more in the form of subsidiaries weakens the diversification benefit of geographic complexity.

Second, the business model as measured by the share of tradable assets to total assets can affect the diversification benefit of geographic spread. Tradable assets often exhibit strongly diversified returns or are issued by large entities which themselves are diversified or have returns less correlated with the domestic business cycle, leaving less space for geographic presence to provide diversification value to the bank. In line with

be in the data (because, say, it has one foreign affiliate), it would still record a low HHI value since its geographic spread would be low, regardless of its high domestic business complexity.

[3] We thank Sebastian Doerr for sharing these data [Doerr and Schaz, 2020].

[4] Shocks to GDP growth are defined as the deviation of actual growth from forecasted growth.

that, we find that a higher share of tradable assets weakens the diversification benefit of geographic complexity.

Third, local economic conditions in the countries where the bank establishes a foreign presence can also be expected to affect the diversification value of geographic complexity. The higher the correlation between economic conditions in home and host countries, the lower should be the ability of a bank to smooth idiosyncratic home country shocks. Indeed, we find that a higher business cycle correlation between home and host locations (implying less diversified economic shocks to borrowers) is linked with a weaker diversification effect.[5]

In the second part of the analysis we turn to local prudential regulatory actions in both home and host countries. These policy actions comprise measures to enhance banks' resilience, such as minimum capital requirements, reserve requirement measures aimed at maintaining a minimum level of liquidity, as well as measures to prevent excessive risk-taking, such as LTV ratio caps (Cerutti et al. [2017]). We find prudential measures to be effective in increasing banks' risk-based capitalization (Tier 1 capital ratio). We do not find evidence that more geographically complex banks exhibit a different degree of capitalization than less complex banks per se. However, we find that the positive effect of regulatory actions on risk-based capitalization is weakened for more geographically complex banks. Just as a wider geographic footprint gives a BHC more room for maneuver in dealing with local shocks, it also allows for a broader range of options to respond to regulation. This can allow the bank to preserve the desired level of risk for the banking group as a whole.

The strength of this channel is linked to the quality of regulation in home and host countries, i.e. locational factors.[6] Our results suggest that if the quality of the regulatory environment is lower (e.g. regulatory enforcement is weak), banks do not need to be geographically complex to circumvent the impact of the regulatory action on their capitalization. This is consistent with our interpretation that geographic complexity enables regulatory circumvention. We do not find strong supporting evidence of business model or organizational factors affecting the relationship between geographic complexity, prudential regulation and bank risk.

[5]This is in line with the results of Goetz et al. [2016] in terms of geographic expansion across metropolitan statistical areas within the United States.

[6]We use the regulatory quality index of the World Bank. We combine the information of this index for the headquarter jurisdiction and all the host jurisdictions in which a BHC has affiliates.

We next split the regulatory actions along two dimensions. The first split is by jurisdiction where the policy is implemented: home country or one of the host countries. The second split refers to the type of prudential regulation, where we summarize all measures in three groups: i) capital regulation (e.g. minimum capital requirements), ii) exposure regulation (e.g. LTV ratio caps), iii) reserve regulation (e.g. minimum local currency reserve requirements). Our results show that geographic complexity helps most in circumventing the impact of exposure regulation in the home country. While it also helps in softening the impact of reserve requirements both at home and in host countries, geographic complexity does not play a significant role in weakening the effect of capital regulation. This suggests that globally coordinated policy frameworks, such as the minimum capital requirements set under Basel III, are effective. Conversely, the impact of truly local prudential regulation is heterogeneous along the dimension of geographic complexity and thus requires more cross-border coordination to be effective in regulating geographically complex global banks.

Throughout the analyses, we leverage our cross-country panel of BHCs to control for potentially confounding factors. Bank fixed effects control for time-invariant bank-specific characteristics, such as the bank's home country or corporate culture. Time fixed effects capture variation that is common to all banks, such as changes in global financial and economic conditions or global risk aversion. We also control for bank-specific time-varying characteristics such as banks' size, profitability, loan portfolio quality, and business model proxies. Finally, we saturate our regressions with $country \times time$ fixed effects. This specification is highly demanding, but it allows us to control for time-varying shocks specific to each headquarter country (e.g. credit demand, regulation, growth, etc.). This goes a long way towards identifying the true effects, but does not allow us to make fully causal claims as the choice of geographic expansion with respect to risk is endogenous, and we cannot control for all bank factors which may correlate with HHI and affect bank risk through GDP shocks or regulatory changes. Nevertheless, our dataset and approach allows us to compare banks with similar geographic complexity, but that are subject to different economic (or regulatory) shocks, as well as banks in the same country (subject to the same shocks), but which differ in terms of their geographic complexity. We thus provide evidence for diversification and regulatory circumvention channels linking geographic complexity with bank risk.

Our paper is the first to empirically link bank geographic complexity with weaker pass-through of regulatory actions on bank capitalization levels in a global setting. The cross-country nature of our dataset allows us to abstract from a single institutional environment (e.g. banks from just one country) and control for time-invariant differences between, as well as time-varying shocks to, individual countries (e.g. regulation or demand). The diversification possibilities afforded to banks by a more complex and wider geographic structure can be both beneficial and detrimental from a financial stability perspective. While complexity allows banks to diversify certain economic shocks, it can also be a countervailing force to the positive effects that regulation can have on riskiness.

Related literature. There is a young but growing literature on bank complexity and bank geographic expansion.[7] Carmassi and Herring [2016], Cetorelli et al. [2014] and Claessens and Van Horen [2014b,a, 2015] among others, highlight the rapidly increasing degree of geographic complexity and reach of banks over the last twenty years, as well as the impact this had on domestic and global market structures. Cetorelli and Goldberg [2014] explores measures of complexity, formulating the geographic HHI used in this paper. Cetorelli and Goldberg [2016] show that the organizational complexity of the family of a bank is a fundamental driver of the business model of the bank itself, as reflected in the management of the banks' own balance sheet.[8]

Closest to ours are papers that examine how the geographic spread or expansion of affiliates affects bank risk. Goetz et al. [2016] uses cross-state differences over time in bank branch regulation as exogenous changes in a bank's ability to expand from one US state to another. They use this with a gravity variable (bilateral for bank and location) to construct an instrument for bank expansion, and show that expanding to areas with less correlated economies reduces bank risk (diversifying their exposure to local shocks).[9] In a sample of 15 European GSIBs, Faia et al. [2019] similarly uses a

[7] This literature does not always position itself explicitly in terms of complexity, as sometimes the focus is on geographic diversification or foreign – or in the case of the US, interstate – expansion. Furthermore, complexity can sometimes also be organizational complexity. We consider these strands of the literature together.

[8] A number of theoretical studies look at the relevance of (geographic) complexity for bank resolution frameworks (Carmassi and Herring [2015], Bolton and Oehmke [2018] and Flood et al. [2017], among others). The measures we develop could also be used to evaluate different resolution approaches.

[9] In related papers, Gropp et al. [2019b] and Bord et al. [2018] examine drivers of bank geographic expansion within the US. Gropp et al. [2019b] show that banks with relatively high locally non-diversifiable risk expand significantly more to other states following the US interstate deregulation of the early 1990s. The riskiness of these banks decreased as they expanded. Bord et al. [2018] show that geographically diverse US banks with low exposure to real estate expanded into new markets in the wake of the 2008 crisis, compared to geographically diverse banks with high exposure to real estate.

gravity variable as an instrument (but without the change in regulation), finding that foreign expansion reduces bank risk. Our paper takes a different approach by taking the bank's pre-existing geographic spread and examining how this affects bank risk in response to unanticipated changes in GDP growth. Importantly, we leverage our unique dataset to provide evidence in a large, global sample of BHCs, which allows us to control for time-varying country specific factors, and establish the relationships in a broader context than these papers. Furthermore, we find three dampening forces to the diversification effect, namely a higher share of countries that banks have access to only through subsidiaries, a higher share of tradable assets, and a higher synchronicity of host and home countries' business cycles (in line with the finding of Goetz et al. [2016] in the case of the US interstate expansion).

Our approach of taking the pre-existing affiliate structure is similar to Krause et al. [2017], who examine how pre-2008 crisis geographic complexity affects bank risk following the financial crisis for a sample of European banks. They find that greater geographic spread increases bank risk for the 2008 shock, potentially through agency problems or exposure to global spillovers (i.e. increasing banks' exposure to and reliance on international financial markets).[10] We establish our results in a larger sample and more generally than the context of 2008.

A few papers show that geographic diversity also improves outcomes via better access to funding. Levine et al. [2019] use the same instrumental variable approach as Goetz et al. [2016] and find that interstate expansion for US banks leads to lower funding costs if the new locations have less similar economic shocks. Doerr and Schaz [2020] use the global syndicated loan market, matched to borrowers and lenders, to control for supply and demand shocks (via lender-time and borrower-time fixed effects) when examining the benefits of diversification. They find that banks with greater geographic exposure in those loans are more likely to maintain their lending to countries experiencing a banking crisis. Such banks appear to have better access to funding which supports the stability in their lending. Our paper focuses on bank-level risk outcomes rather than credit supply. These papers provide valuable context and complementary evidence to our findings.

There is also a growing body of literature on global banks' ability to circumvent regulation through their international network of affiliates. Using global data from the BIS

[10]Other studies have shown higher geographic diversification can lead to higher exposure to shocks in foreign markets [Berger et al., 2017], a loss of market power in the domestic market [Buch et al., 2012], and higher systemic risk [Chu et al., 2020].

consolidated banking statistics, Houston et al. [2012] show that banks lend more to borrowers in locations with less stringent banking regulations. Berrospide et al. [2017] also look at the effect of regulation on lending, but with a focus on banks in the US. A tightening of foreign prudential policy leads to an increase in US lending by both domestically owned global banks and by US affiliates of foreign banks. Foreign tightening of capital requirements also shifts lending by US banks from that location to other locations where these banks operate. A tighter regulation at home, in turn, induces US banks to reduce their lending abroad. Focusing also on US banks, Temesvary [2018] makes the case for the existence of regulatory arbitrage by showing that US banks lend less to borrowers in host countries with stricter bank regulations, are less likely to maintain affiliates in such countries, and substitute from host-regulated affiliate towards US-regulated cross-border lending in host countries with strict bank capital rules. Our papers differs from these contributions in that: (i) we focus on measures of bank risk rather than bank lending outcomes, (ii) we examine specifically the geographic spread of banks' foreign affiliates (as captured by the HHI) and connect this to bank risk, and (iii) we analyze a global panel of large internationally active banks. Further, we show that reserve requirements and exposure regulation (e.g. interbank exposure limits) are the main types of regulation for which geographic complexity loosens the impact.

The analyses in our paper bridge the literature on the effect of bank geographic diversification on bank risk and the literature on how global banks deal with changes in regulation. Our results corroborate the key findings from these two strands of the literature. We make a further, important contribution to the literature by simultaneously showing with the same dataset that bank geographic complexity can be good in terms of shock diversification, but can also alter the impact of prudential regulatory measures on bank risk. Moreover, we establish these results in a novel, global sample of banks, showing the importance of the geographic spread of their affiliates, and digging into channels that amplify or mitigate geographic complexity's role.

Roadmap. The remainder of the paper proceeds as follows: Section 3.3 describes the dataset and its construction; Section 2.3 goes into details of our HHI measure and its economic interpretation, Section 2.4 describes the empirical approach and discusses the results; and finally, Section 4.7 concludes.

2.2 Data

We build a novel dataset on the complexity of internationally active banks using the *BIS Banking List*. As part of the International Banking Statistics (IBS), the BIS annually collects information on the internationally active bank entities that report to the BIS locational banking statistics. As of end-2016, this banking list contained 8331 banking entities. For each year and bank, the list has information on the country from which the bank is reporting, the type of institution (i.e. branch, subsidiary, domestic bank, etc.), and the name and nationality of the controlling parent, among other items.

We build a measure of bank complexity in the spirit of Cetorelli and Goldberg [2014], within the constraints of our dataset.[11] The subsidiaries and branches in our data are internationally active banking entities. Thus, they are a subset of all BHC's affiliates, as we do not have information about non-bank affiliates or domestically oriented affiliates. Nevertheless, they have the advantage of focusing on the international aspect of the BHC's operations.[12]

The main complexity variable we construct is a geographic Herfindahl-Hirschman index based on Cetorelli and Goldberg [2014]:

$$HHI = 100\frac{R}{R-1}\left(1-\sum_{j=1}^{R}\left(\frac{Affiliates_j}{TotalAffiliates}\right)^2\right) \tag{2.1}$$

$Affiliates_j$ is the number of affiliates that the bank has in location j. R is the total number of countries in which any bank has affiliates in our sample. $TotalAffiliates$ is the total number of affiliates the bank has across all regions. Larger values in this index indicate higher complexity. If all of a bank's affiliates are located in a single country, this measure would record a zero, the lowest value. If each of a bank's affiliates operate in a different country, this measure would record one hundred, the highest value. Thus, the information captured by this metric is different from – and complementary to – information obtained from measures based on plain counts of affiliates or host countries. Since this measure accounts for concentration of affiliates in each location, it has

[11] Figure 2.A.1 in Appendix 2.A presents a stylized description of the banking list in its raw format and the transformations we apply before building measures of complexity.

[12] Furthermore, the extent of geographic diversity is bound by the number of countries which contribute to the BIS statistics and provide a banking list. Hence, the total number of affiliates reported will be a minimum for the BHC's banking affiliates or its total affiliates.

the advantage that it captures geographic complexity separately from the size of banks' organizational structure.

To measure bank risk, we look at balance sheet based measures.[13] In particular, we focus on the z-score when analyzing economic shocks. This is computed as $\frac{ROA+Equity/Assets}{sd(ROA)}$, where ROA is the return on assets. In line with the literature, and in order to interpret increases in the indicator as higher bank risk, we take the inverse of the logarithm of the z-score. When analyzing regulatory changes, we focus on a measure of bank capitalization, computed as: $1 - regulatory\ Tier1\ capital\ ratio$ (i.e. higher values indicate less capitalization and hence higher risk).

The risk indicators we consider capture different aspects of risk. The z-score, which is the most commonly used measure of bank risk, can be thought of as a proxy for realized risk. The ratio between Tier 1 capital and risk-weighted assets comes closest to an ex ante measure of risk.

Our dataset has a yearly frequency, runs from 2008 to 2016 and comprises 96 BHCs headquartered in 22 countries.[14] A significant number of banks in our sample are part of the GSIB assessment sample: as of end-2016, 68 of the 76 BHCs that make up the GSIB assessment sample are part of our dataset.[15] Nearly all banks designated as GSIBs are included in our sample.[16]

We match our data at the BHC-year level with balance sheet data from Fitch. We also incorporate country-level data on macroprudential regulations from the IBRN database (Cerutti et al. [2017]), as well as additional macroeconomic indicators. Tables 2.A.1 and 2.A.2 present all variables used in the paper, their definition and source.

2.2.1 Data summary

Table 2.2.1 summarizes the descriptive statistics for two types of geographic complexity measures, namely the HHI as specified in Equation 2.1, and count and share measures.

[13] All bank-specific variables – including the HHI – are winsorized at the 1/99% level.

[14] The distribution by country (number of banks) is as follows: AT (1), AU (4), BE (2), BR (3), CA (5), CH (2), CN (12), DE (7), DK (1), ES (4), FI(1), FR (7), GB (6), IN (1), IT (4), JP (7), KR (4), NL (2), NO (1), RU (2), SE (3), SG (2), US (15). We have banks headquartered in six emerging markets in our sample, namely Brazil, China, India, South Korea, Russia and Singapore. Our definition of emerging markets follows that of the BIS.

[15] Chinese banks that are not GSIBs, yet are part of the GSIB assessment sample, are not part of our dataset.

[16] The exceptions are Wells Fargo and Dexia. Dexia was part of the first list of GSIBs published in 2011 but was removed in 2012 (never to return) when it started undergoing an orderly resolution process.

We look at the time series behaviour as well as regional differences to highlight the importance of a cross-country panel approach to bank complexity and risk.

The first two rows in the upper panel of Table 2.2.1 compare the distribution of HHI values at the beginning and end of the sample. While the mean goes down only marginally, the standard deviation goes up considerably. That is, even though there is no overall trend, there seem to be heterogeneous developments in complexity.

Rows three to six in the upper panel of Table 2.2.1 show regional differences at the end of our sample. US banks show high dispersion – with banks both at the higher and lower ends of the spectrum – but a comparably low mean. Euro area banks, instead, appear to be significantly more complex and exhibit a lower degree of dispersion. Banks from other advanced economies seem to reside in the middle of the two extremes. Finally, banks from emerging markets exhibit a relatively low average HHI but a relatively high dispersion (second only to that of US banks). The HHI of the median bank does not vary much over time as can be seen by the standard deviation in the seventh row of the upper panel of Table 2.2.1. The modest time series variation for some individual banks highlights the importance of exploiting the cross-sectional differences interacted with various time varying factors.

The lower panel of Table 2.2.1 focuses on count and share measures. The share of foreign branches in the overall network structure has only slightly moved up over our sample (first and second rows). The share of foreign subsidiaries, in turn, has gone down (third and fourth rows). Rows five and six highlight the growth in the share of affiliates in EMEs over our sample period. The next four rows present descriptive statistics on the number of branches and subsidiaries at the beginning and end of our sample. In line with the shares, we observe a rise in the number of branches, and a somewhat more moderate decline in the average number of subsidiaries. The last two rows of the lower panel look at the number of host countries a bank is present in. This number rose slightly, again with a notable increase in dispersion. Together with the statistics on subsidiaries and the HHI, this suggests that some banks closed down subsidiaries abroad while others even increased their complexity by expanding to new countries, leading to a larger variance in the HHI.

Table 2.2.2 presents summary statistics for the main bank-specific variables other than the HHI. Size – measured as the logarithm of total assets – as well as the return on assets, show that we have a rather uniform set of very large and profitable banks. US banks tend to be a bit smaller than euro area banks at the beginning of the sample, but

Table 2.2.1: Geographic complexity - descriptive statistics

	Mean	Median	Min	Max	Std
HHI 2008	85.27	87.80	44.83	97.07	10.47
HHI 2016	83.96	88.90	50.43	97.44	12.88
HHI 2016 US	80.66	86.60	50.43	97.44	16.86
HHI 2016 EA	87.41	91.65	50.43	95.78	10.21
HHI 2016 AE - other	84.86	88.35	52.61	95.19	10.84
HHI 2016 EME	81.39	87.02	50.43	95.71	14.55
HHI median Time Series	87.68	88.03	86.74	88.58	0.75
Share of Branches 2008	0.56	0.57	0.00	1.00	0.19
Share of Branches 2016	0.59	0.58	0.00	1.00	0.23
Share of Subs 2008	0.36	0.33	0.00	1.00	0.23
Share of Subs 2016	0.29	0.26	0.00	1.00	0.22
Share of EME affiliates 2008	0.07	0.00	0.00	0.38	0.09
Share of EME affiliates 2016	0.19	0.19	0.00	1.00	0.17
No of Branches 2008	9.76	7.00	0.00	62.00	9.92
No of Branches 2016	10.51	7.00	1.00	58.00	9.63
No of Subs 2008	5.90	3.00	0.00	33.00	6.51
No of Subs 2016	5.78	4.00	0.00	36.00	6.59
No of Countries 2008	11.93	10.00	2.00	33.00	7.56
No of Countries 2016	12.95	11.00	2.00	37.00	8.96

converge towards the end of the sample. They are significantly more profitable than euro area banks (and so are banks from other jurisdictions). Euro area and emerging market banks seem to have a lower quality of their loan portfolio as indicated by the higher values of loan loss reserves (column three). In general, banks have very different structures in terms of reliance on deposit funding and loan business (columns four to six). This highlights the richness of our data, as we can observe banks with different business models across countries.

Table 2.2.2: Bank variables - average for region × year

	Size	ROA	LLR	Loans	Sec	Dep	Z-score	Cap	Trad.Ass.
US 2008	12.83	0.37	0.80	44.70	32.95	55.09	0.60	0.88	7.57
US 2016	13.08	1.61	0.65	42.33	34.57	57.93	0.35	0.86	7.64
EA 2008	13.55	0.10	1.61	50.16	34.75	30.86	0.50	0.92	11.39
EA 2016	13.18	0.37	2.93	52.63	31.04	40.25	0.44	0.84	5.89
AE - other 2008	13.34	0.18	0.64	49.53	38.05	43.41	0.46	0.91	11.73
AE - other 2016	13.46	0.65	0.59	49.72	33.67	50.22	0.36	0.83	9.25
EME 2008	12.61	1.06	1.47	54.55	25.36	63.07	0.51	0.90	0.92
EME 2016	13.48	1.24	1.41	53.74	28.89	56.62	0.40	0.88	3.84

Notes: *Size* is measured as the logarithm of total assets. *ROA* is the return on assets, expressed as percentage. *Loans*, securities (*Sec*) and deposits (*Dep*) are all expressed as a percentage of total assets. *LLR* stands for loan loss reserves over total loans multiplied by 100. *Z-score* stands for 1/log(z-score). *Cap* stands for 1 - Tier1 Capital Ratio. *Trad.Ass.* stands for trade-able assets as a percentage of total assets.

The riskiness of the banks in our sample – as measured by the z-score – varies significantly over the sample period. Euro area banks, which started from almost the lowest level of riskiness at the beginning of the sample, are by a good margin the riskiest banks at the end of the sample. Lastly, the capitalization variable indicates that banks in our sample are well capitalized. That said, we also observe quite some variation in this measure, where the general trend shows that average capitalization rates have gone up considerably over time. Additional summary statistics for our main variables can be found in Table 2.A.3 in the Appendix.

2.3 Determinants of the Herfindahl-Hirschman index

Our measure of geographic complexity contains information which differs from, and complements that, defined in the GSIB framework. The BCBS defines complexity as the simple average of scores calculated using the notional amount of OTC derivatives, level 3 assets[17], and trading as well as available-for-sale securities. This measure therefore captures operational complexity.

Figure 2.3.1, Panel 1 compares our geographic complexity variable (HHI) with the BCBS complexity variable as of end-2016; the correlation between the two is 0.36.[18,19] For banks in the lower spectrum of complexity as defined by the BCBS (score roughly below 200), the HHI measure of geographic complexity provides much more variation and allows for an additional layer of differentiation between banks. In the top-right corner of the figure, both measures align in pointing to the most complex banks.

Our paper makes a case for considering affiliate-based geographic complexity when assessing the relationship between bank complexity and risk. The BCBS framework provides other bank complexity indicators that could be associated with our HHI measure, namely cross-jurisdictional activity, interconnectedness and size. Panels 2 to 4 in Figure 2.3.1 present scatter plots for each of these, respectively. They exhibit a slightly higher correlation with HHI, all around 0.44. The strong correlation of these and other complexity measures with our measure validates the relevance of our measure of bank complexity. However, the scatterplots underscore the valuable additional variation that the HHI offers, especially for banks in the lower spectrum of these other complexity measures. All four panels point to a slightly non-linear relationship between the HHI and other measures of complexity.

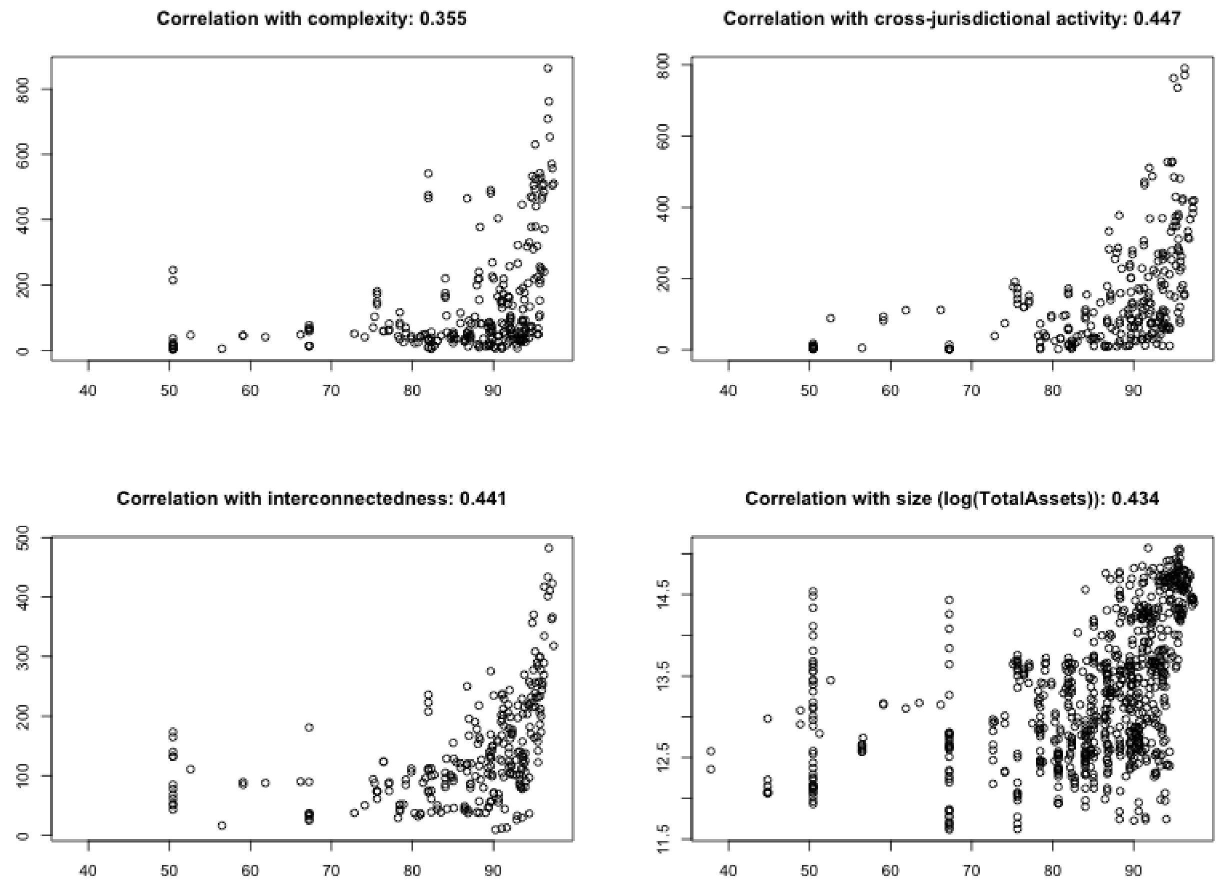
We more formally examine how geographic complexity – as captured by the HHI – co-moves with other bank-level variables by running the following regression:

$$HHI_{it} = \alpha_t + \alpha_i + \boldsymbol{\gamma}\mathbf{X}_{it} + \epsilon_{it} \tag{2.2}$$

where i indicates the banking group, t indicates time and $\mathbf{X}_{it}$ is a vector of contemporaneous bank-specific variables. This includes measures of: size (logarithm of total assets), profitability (return on assets), loan portfolio quality (loan loss reserves over total loans), loans to assets, deposits to assets and securities to assets. Moreover, we use all five indicators used in the GSIB assessment (size, cross-border activity, interconnectedness, substitutability, complexity) and the geographic complexity of the syndicated

[17]Level 3 assets are banks' most illiquid assets, making them more opaque and difficult to value.
[18]The figure shows the BCBS complexity score for those banks that are part of the GSIB assessment sample.
[19]Figure 2.A.4 shows the bilateral correlations across various complexity measures, both raw and after removing bank fixed effects.

Figure 2.3.1: HHI geographic complexity vs. alternative complexity measures



Note: each panel plots our HHI measure on the x-axis versus the respective BCBS or balance sheet indicator on the y-axis.

lending portfolio as measured by Doerr and Schaz [2020]. We include time fixed effects (α_t) and bank fixed effects (α_i) in all regressions. The former control for global shocks that are common to all banks which may affect their complexity, such as broad-based changes in global financial or regulatory conditions. Bank fixed effects, in turn, control for bank-specific levels of complexity that do not vary over time, due to, e.g., differences in corporate culture or time-invariant business model characteristics.

The results are presented in Table 2.3.1. Starting from a fixed effects-only specification in column (1), we sequentially add variables to gauge the extent to which the variation in HHI can be explained by those factors. To cleanly measure the additional explanatory power of the added variables, we run our regressions in columns (1) to (4) and in columns (5) and (6) on two separate constant samples (the latter incorporating the GSIB assessment variables). Since the HHI is a very slow moving measure, bank- and time-fixed effects alone explain 95.7% of the observed variation. Adding size (second column) only explains 2.5% of the *remaining* variation (i.e. the R^2 only rises from 95.7% to 95.8%), with the coefficient on size being statistically insignificant. In column (3) we also include the geographic diversity of the syndicated loan portfolio from Doerr and Schaz [2020] (DS), which explains roughly 1% of the *remaining* within-bank HHI variation; the R^2 thus increases slightly, but neither the DS indicator nor size are statistically significant. Note that size and HHI have a bilateral correlation coefficient of 0.43, which shrinks to 0.11 after controlling for bank fixed effects. In a regression without bank fixed effects, size is a significant predictor of HHI.[20] The R^2 increases only slightly with the addition of information on profitability, quality of the loan portfolio, and loans-, securities-, and deposits-intensity of the banks' balance sheets. Adding the GSIB indicators significantly shrinks the sample size, especially in the time dimension, capturing only three years of data. In this sample, the same sets of fixed effects and explanatory variables used in column (4) explain 99.6% of the variation of the HHI (column (5)). Adding the GSIB indicators explains roughly 25% of the remaining within-bank variation (column (6)).

Taking these results together, we are confident that our measure captures information distinct from that contained in the alternative indicators considered. To underpin this assertion, we reproduced the regressions presented in the following section using either size, GSIB complexity or the Doerr and Schaz [2020] indicator as the measure of

[20]Similarly, the DS indicator has a raw correlation with HHI of 0.51, but only -0.03 after removing bank fixed effects. The other measures also have low correlations with each other after controlling for bank fixed effects. See Figure 2.A.4.

Table 2.3.1: Determinants of HHI

	(1)	(2)	(3)	(4)	(5)	(6)
Size_{it}		2.048	2.273	1.503	1.002	1.981
		(1.416)	(1.453)	(1.326)	(1.222)	(1.351)
DS_{it}			-3.253	-3.925**	-0.418	-1.157
			(2.056)	(1.959)	(2.369)	(2.383)
Loans_{it}				-7.897	-7.039*	-6.674*
				(5.543)	(3.723)	(3.746)
Securities_{it}				-1.931	5.233	4.148
				(4.823)	(3.458)	(3.002)
Deposits_{it}				-8.083	10.66**	10.41**
				(6.127)	(5.198)	(4.921)
ROA_{it}				4.546	25.04	29.32
				(27.31)	(26.06)	(24.68)
LLR_{it}				0.146	52.01	59.71
				(34.42)	(41.67)	(36.66)
GSIB Size_{it}						-0.000922
						(0.00701)
GSIB $\text{CrossborderActivity}_{it}$						-0.0142**
						(0.00655)
GSIB $\text{Interconnectedness}_{it}$						0.00142
						(0.00364)
GSIB $\text{Substitutability}_{it}$						0.000927
						(0.00496)
GSIB Complexity_{it}						0.00300
						(0.00287)
Observations	614	614	614	614	172	172
R^2	0.957	0.958	0.958	0.959	0.996	0.997
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes
Banks	81	81	81	81	59	59

Notes: Results from estimating Equation 2.2. HHI is the Herfindhal-Hirschman index, DS is the geographic diversification of the syndicated lending portfolio from Doerr and Schaz [2020]. $Size$ denotes the logarithm of total assets. $Loans$, $Securities$ and $Deposits$ are normalized by assets. LLR stands for loan loss reserves normalized by total loans. ROA stands for the return on assets. Variables starting with $GSIB$ denote the indicators from the BCBS.

complexity. These results, available in the online appendix, do not match our baseline results using the HHI, highlighting the latter's unique economic information which we leverage in our analysis.

2.4 Results

2.4.1 Complexity and local shocks

The complexity of a bank holding company can help the organization dampen the effect of economic shocks. In particular, if shocks occur in the country of headquarters, a broader geographic footprint could act as a shock absorber or mitigant. When viewed in this light, geographic complexity can be alternatively thought of as providing diversification value to the organization.

In this section we look at how BHCs cope with shocks in their home country and the role that bank complexity plays in affecting the link between these local shocks and bank risk. We test if the diversification benefit of geographic complexity helps shield bank risk from domestic economic shocks. To do so, our baseline regression takes the following form:

$$z\text{-}score_{it} = \alpha_t + \alpha_i + \beta_1 HHI_{it-1} + \beta_2 GDP\_Shock_{it} + \beta_3 GDP\_Shock_{it} \times HHI_{it-1} + \boldsymbol{\gamma}\mathbf{X}_{it-1} + \epsilon_{it} \tag{2.3}$$

with HHI as defined before. The vector of controls $\mathbf{X}_{it-1}$ contains lagged values of the bank balance sheet variables employed in column (4) of Table 2.3.1. Our outcome variable is the $z\text{-}score_{it}$, expressed as the inverse of the log value so that higher values indicate higher risk. The z-score compares return on assets and capitalization to the volatility of returns to create a metric which can be interpreted as distance to default. Risk increases when returns become more volatile, when returns fall, or if capitalization falls. GDP_Shock_{it} is a measure of the local economic shock (i.e. the shock in the country of headquarters of BHC i). It is defined as the difference between the realized annual real GDP growth and the consensus forecast of GDP growth for the same year; a negative GDP shock thus indicates actual real GDP growth falling short of expectations.[21]

[21] The forecast of GDP growth is taken from the OECD Economic Outlook. It is based on an assessment of the economic climate in individual countries and the world economy, using a combination of model-based analyses and expert judgement. Forecasts are done twice a year, for the next two years.

After controlling for time invariant bank factors, common shocks, and time varying bank controls, our identification assumes that banks differ in how their risk is affected by a GDP shock only by their level of geographic complexity. We further sharpen this by including country-time fixed effects, controlling for all time-invariant and time-varying country level shocks, such as (changes in) economic conditions or policies, which may correlate with both GDP shocks and bank risk in a given country. The factors working towards identification are that banks' geographic structure is generally slow moving (not likely to immediately react to transitory GDP shocks), we take its lagged value (before the shock occurs), and we interact it with shocks to GDP which were unanticipated (i.e. not forecasted) and so plausibly exogenous to the bank. Country-time fixed effects account for further channels by which the GDP shock affects average bank risk in the country.

In general, the choice of geographic complexity is endogenous to the bank's risk profile. The main threat to identification is bank characteristics which are correlated with HHI and can differentially affect how GDP shocks transmit to bank risk. More profitable banks may be the ones who have the opportunity and incentive to expand, and those with falling profits may be forced to close affiliates abroad. We check this for some observable characteristics, but there may be other (potentially unobservable) bank characteristics which matter for this relationship. Thus, we do not fully establish causality in our results. Nevertheless, our global sample allows us to compare banks with similar characteristics and geographic complexity (and thus similar propensities for profit and risk), that differ in terms of their exposure to GDP shocks (cross-country variation), as well as banks with similar characteristics and identical exposure to domestic conditions, that differ in terms of their geographic complexity (within-country variation). The combination of the two provides a meaningful window into the importance of HHI in determining the effects of GDP shocks on banks risk.

The result from estimating Equation 2.3 is presented in column (1) of Table 2.4.1.[22] A negative GDP shock does indeed drive up bank risk, as indicated by the negative and significant coefficient on GDP_Shock (β_2). However, the positive and significant coefficient on the interaction term indicates that BHC complexity can help mitigate this effect. While the mean of the GDP shock is almost zero (indicating small average fore-

[22] All specifications control for time fixed effects, thereby absorbing truly global variation such as may be driven by events like the great financial crisis of 2008-2009. In results found in the online appendix, we include dummies for the great financial crisis and for the European sovereign debt crisis along with all relevant interaction terms. Our key results are not driven by these events.

cast errors), a standard deviation shock of -0.138 percentage points to GDP increases the risk of an average bank by roughly 10.8%. Each additional point of HHI reduces this effect by roughly 0.25 percentage points. The way the measure is constructed implies that banks that either have a larger overall foreign affiliate network, a larger geographical reach, or a more evenly spread distribution of affiliates across host countries, can buffer a home country shock more easily. All these factors help in diversifying income, while expanding the affiliate network at home, e.g. by opening additional domestic affiliates, will not give the BHC access to other income sources than its headquarter already grants. Column (2) adds country-time fixed effects to this specification. We see that with this added saturation, the results actually sharpen. The coefficient estimate of the interaction term increases slightly in size and strongly in statistical significance. In the online appendix, we examine if our other bank controls (size loans, ROA, etc.) drive the results. Including these as competing interactions with the GDP shock variable does not affect the significance of the HHI interaction.

To better understand the way geographic complexity interacts with local economic shocks, we next drill into the heterogeneity of this link across banks with similar geographic complexity. The diversification value of a greater geographic spread could depend on the type of affiliates the BHC has abroad (organizational factors), the dependence of the BHC's balance sheet on specific assets (business model factors), or the characteristics of the host countries which the BHC chose to expand to (locational factors). We tackle each of these in turn.

The flexibility given to BHCs by their geographic complexity is likely to be affected by the types of foreign affiliate the bank chooses. Concretely, the ease with which business and resources can be shifted to affiliates abroad for the purpose of smoothing shocks depends on the type of affiliates. Banks can choose to go abroad via branches or subsidiaries (Cerutti et al. [2007]). Subsidiaries are locally chartered (i.e. in host jurisdictions), are separately capitalized, typically report earnings on a standalone basis and are regulated by host country entities. Branches, on the other hand, are not independently capitalized, do not have an independent balance sheet, can be limited in their ability to raise local retail (insured) funding and are regulated by entities in the home jurisdictions where the BHC is headquartered. Branches should therefore provide more flexibility in the reallocation of business and funds within the banking organization. To test the importance of the affiliate type, we construct a variable that measures the share of countries within the host network that banks *only* have access to through subsidiaries.

If a bank has access to a country through both branches and subsidiaries, it is impossible to disentangle the diversification benefit of the branch and the subsidiaries. Hence, we compare countries where banks have only subsidiaries to countries where banks have at least one branch. Indeed, the larger the share of countries a bank has access to only through subsidiaries, the less geographic complexity mitigates the impact of local shocks on bank risk (column (3)). The interaction term is negative, but not significant. Once country-time fixed effects are controlled for (column (4)), the results sharpen distinctly with the coefficient tripling in size and exhibiting statistical significance at the 5%-level.[23]

The relationship between geographic complexity and bank risk may interact with the bank's business model. That is, the type of assets banks hold on their balance sheet might be an indicator of how well they can make use of their geographically diversified affiliate network. We test specifically if banks potentially benefit less from the diversification benefit if more of their assets are tradable. Trading assets are typically issued by entities which are large and more diversified themselves (either in geography or industry), so their return may carry diversification value which minimizes the additional benefit of the geographic spread. Indeed, in column (5) we find a positive and significant coefficient on the double interaction of trading assets with the shock, indicating the diversification benefit of these assets. The significant and negative triple interaction shows evidence that a higher share of tradable assets impairs the diversification value of higher foreign affiliate HHI. This coefficient drops in size and significance, however, in the more demanding country-time fixed effects specification in column (6). Note that the direct effect ($HHI \times GDPshock$) remains significant in both.

[23]Banks with more loan business may also expand abroad more in the form of subsidiaries, potentially confounding the relationship. In results reported in the online appendix, we perform a horse race with a loans to assets interaction, and find that the subsidiary share results are not driven by this factor.

Table 2.4.1: Local Economic Shocks, Geographic Complexity and Bank Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI_{it-1}	0.00120	-0.000343	0.00405**	0.00354*	-0.000555	-0.00120	-0.000663	-0.00160
	(0.00124)	(0.00109)	(0.00198)	(0.00182)	(0.000941)	(0.00128)	(0.00178)	(0.00162)
GDP Shock_{it}	-1.528*		-3.186		-2.306**			
	(0.837)		(1.959)		(0.991)			
$\text{HHI}_{it-1} \times \text{GDP Shock}_{it}$	0.0173*	0.0206***	0.0358	0.0813*	0.0254**	0.0258***		
	(0.00970)	(0.00671)	(0.0230)	(0.0453)	(0.0116)	(0.00743)		
$\text{SubCountryShare}_{it}$			0.668**	0.493*				
			(0.319)	(0.287)				
$\text{HHI}_{it-1} \times \text{SubCountryShare}_{it}$			-0.00765*	-0.00566				
			(0.00390)	(0.00354)				
$\text{GDP Shock}_{it} \times \text{SubCountryShare}_{it}$			5.523	17.19**				
			(4.172)	(8.577)				
$\text{HHI}_{it-1} \times \text{GDP Shock}_{it} \times \text{SubCountryShare}_{it}$			-0.0625	-0.211**				
			(0.0510)	(0.105)				
$\text{TradingAsssets}_{it-1}$					-1.227*	-1.059		
					(0.658)	(0.955)		
$\text{HHI}_{it-1} \times \text{TradingAsssets}_{it-1}$					0.0142*	0.0144		
					(0.00760)	(0.0117)		
$\text{GDP Shock}_{it} \times \text{TradingAsssets}_{it-1}$					41.21**	10.22		
					(18.17)	(14.49)		
$\text{HHI}_{it-1} \times \text{GDP Shock}_{it} \times \text{TradingAsssets}_{it-1}$					-0.459**	-0.143		
					(0.202)	(0.158)		
GDP Growth_{it}							-0.0308	
							(0.0235)	
$\text{HHI}_{it-1} \times \text{GDP Growth}_{it}$							0.000334	0.000528*
							(0.000301)	(0.000313)
GDP Corr_{it}							-0.247**	-0.190*
							(0.114)	(0.107)
$\text{HHI}_{it-1} \times \text{GDP Corr}_{it}$							0.00223*	0.00257*
							(0.00133)	(0.00143)
$\text{GDP Growth}_{it} \times \text{GDP Corr}_{it}$							0.0470*	0.0293
							(0.0237)	(0.0207)
$\text{HHI}_{it-1} \times \text{GDP Growth}_{it} \times \text{GDP Corr}_{it}$							-0.000519*	-0.000494
							(0.000308)	(0.000326)
Observations	639	584	576	533	464	415	582	533
R^2	0.730	0.897	0.878	0.943	0.687	0.901	0.873	0.938
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	No	Yes	No	Yes	No	Yes	No
CountryTimeFE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks	79	73	79	73	73	67	79	73

Notes: The dependent variable is bank risk, measured as the inverse of the logarithm of the z-score (higher values indicate higher risk). Sample consists of annual data from 2008 to 2016. HHI is the geographic Herfindahl-Hirschman index for the bank's foreign affiliates. GDP Shock is the deviation of real GDP growth from actual for the bank's headquarter country. SubCountryShare is the share of countries that a bank only has access to through subsidiaries. TradingAssets is the share of tradable assets in total assets. GDP Corr is the average correlation (weighted by number of affiliates) of GDP growth between the headquarter country and the countries in which the bank has affiliates. All control variables (Size, Loans, ROA, loan loss reserves (LLR), Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. LLR are normalized by lagged total loans. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

The precise locations where banks expand to may also be relevant for the HHI-risk relationship. For instance, the similarity of economic conditions in the home country and the host countries may also affect the diversification benefit. The geographic spread of a bank is likely to be less helpful if the host countries it operates in experience similar shocks and their business cycles correlate strongly with that of the bank's home country. In columns (7) and (8) of Table 2.4.1, we slightly change the specification of column (1) by replacing GDP shocks by raw GDP growth and including a variable capturing the weighted correlation between the real GDP growth of the country in which bank i is headquartered and the real GDP growth of all the host countries.[24] The weights are given by the number of affiliates per host country (i.e. a high value indicates that the business cycle of the country in which bank i is headquartered is similar to the business cycles of the countries in which the bank is present through affiliates). In addition, we include interactions of this variable with our measure of geographic complexity.

As shown by the triple interaction term, the larger the correlation between the business cycles of home and host countries, the less bank complexity provides a cushion for the effect of local shocks on bank risk. This result shows that the value of geographic complexity is reduced (increased) when the business cycles of host countries are on average more (less) correlated with that of the home country. This result extends the finding from Goetz et al. [2016] to an international context. The magnitude of this result drops only slightly when country-time fixed effects are included, though this is enough to reduce the statistical significance just below the 10% level.

Taking stock, we document that a more geographically complex affiliate network helps banks mitigate the impact of adverse economic shocks in the country of headquarters on their idiosyncratic risk. This effect is weaker for banks who expand more via subsidiaries (organizational factors), whose balance sheet is more dependent on tradable assets (business model factors), and whose host countries have business cycles which are more strongly aligned with that of the home country (locational factors).

2.4.2 Complexity and home/host prudential regulation

This section examines how bank geographic complexity affects the impact of regulation on risk. Specifically, we test if changes to prudential regulation have less of an impact

[24] We switch to GDP growth to match the economic concepts of our shock variable and the variable for which we calculate the correlation across the business cycle network. A correlation of shocks as defined before would imply looking at a correlation of forecast errors, which is not the relevant economic concept.

on risk for banks with greater geographical spread. We look at prudential regulation in both the country of headquarters as well as the different host countries in which a BHC is present through its affiliates. A more geographically complex bank has a broader range of options to respond to regulations, with potentially negative implications for financial stability.[25] With the shift from economic shocks to regulation, we also modify our left-hand side variable to focus on risk-weighted bank capitalization, as this is a key target measure of regulators that proxies an ex-ante perspective of bank risk. A better capitalized bank is, other things equal, a less risky bank.

Our baseline specification is:

$$\begin{aligned} bank\_cap_{it} = {} & \alpha_t + \alpha_i + \beta_1 HHI_{it-1} + \beta_2 Pru.Reg_{it-1} + \beta_3 HHI_{it-1} \times Pru.Reg_{it-1} \\ & + \boldsymbol{\gamma}\mathbf{X}_{it-1} + \epsilon_{it}, \end{aligned} \tag{2.4}$$

where $bank\_cap_{it}$ is 1 minus the regulatory Tier 1 capital ratio (e.g. higher values indicate less capitalization, more leverage, higher risk). $Pru.Reg_{it-1}$ captures the changes in prudential policies in year $t-1$, combining both home (i.e. headquarter) and host countries. A tightening of one policy is captured by +1, a loosening by a -1, and no change is captured by 0.[26] We use the database on prudential regulations from Cerutti et al. [2017] and combine information from all policy actions. These policy actions include measures aimed at strengthening banks' resilience, such as increases in minimum capital requirements, as well as measures aimed at reducing risk-taking, such as LTV ratio caps. The rest of the elements of Equation 2.4 are as in the previous regressions.

Our identification assumptions are similar to those in Section 2.4.1. Controlling for global shocks (time fixed effects), time-invariant bank factors (bank fixed effects), and time-varying bank characteristics, our approach assumes that banks differ in how their capitalization is impacted by regulation changes only by their level of geographic complexity. We further refine this by including country-time fixed effects, which capture time-invariant and time-varying factors in the country of headquarters, including policy changes, which can affect banks' capitalization as well as their propensity to ex-

[25] In addition to altering the balance sheet impact of regulation, bank complexity can also be detrimental to financial stability by making resolution more complicated (Bolton and Oehmke [2018]). We do not investigate this aspect here.

[26] A 50% weight is given to headquarter and host country policy changes. Host country changes are in turn the affiliate-weighted average of the policy changes in the countries in which the bank has foreign affiliates.

pand/contract abroad. As with the economic shock analysis, we draw both from cross-country as well as within-country variation to shed light on the role of geographic complexity in the nexus between regulation and risk-weighted capitalization.

While changes in prudential regulation are plausibly exogenous to an individual bank (especially when controlling for country-time fixed effects), they are more likely to be anticipated by banks and may be implemented precisely because banks are risky or poorly capitalized.[27] Still, as with the previous section, the main threat to identification in our setup relates to bank specific factors correlated with HHI which differentially affect how regulation impacts bank capitalization. We again check this for observable characteristics, but cannot rule out other (potentially unobservable) bank characteristics. While this evidence goes a long way in identifying the underlying effects, we therefore do not interpret our estimates as fully causal.

Table 2.4.2 summarizes the results. As shown in columns (1) and (2), a tightening of prudential regulation is associated with an increase in bank capitalization, indicating that the regulation is indeed having an effect towards reducing bank risk. However, geographic complexity weakens this effect. More complex banks appear to find alternative adjustments besides their capitalization in response to regulatory tightenings in the jurisdictions where they operate. A standard deviation increase in regulatory tightening raises the risk-weighted capitalization of an average bank by 0.63%-points. Each additional unit of HHI dampens this effect by approximately 0.07%-points.[28]

It is plausible to argue that more geographically complex (high HHI) banks are more closely scrutinized and therefore build capital buffers earlier than other banks in the sample. When regulatory changes are introduced, these international banks would then simply reduce their buffers (or keep their capital constant) and be seen in the data to respond less than their less complex peers. However, if this were the case we should see a correlation between HHI and capitalization, captured by the coefficient on the non-interacted HHI in the first row of Table 2.4.2. In no specification is this coefficient statistically significant. There is thus no evidence that high HHI banks show a different degree of capitalization than less complex banks. In results reported in the online appendix, we examine if our other bank controls (size, loans, ROA, etc.) drive the results

[27] Even when anticipated, banks might not quickly change the geographic structure of their affiliates in response to most prudential actions, as such moves are costly.

[28] Banks at the higher end of the geographic complexity spectrum in our sample are able to fully avoid the balance-sheet impact of the regulatory action and keep their capitalization constant.

over HHI. Including these as competing interactions with Pru. Reg. does not affect the significance of the HHI interaction in nearly all specifications.[29]

As documented in Section 2.4.1, the effect of geographic complexity on bank risk depends to some extent on organizational, business model and locational factors. We next investigate whether these factors also affect the way in which geographic complexity interacts with regulation in affecting bank risk.

We start with organizational factors. In columns (3) and (4), we again include the share of countries a BHC has access to only through subsidiaries as an interaction term. The point estimates for the triple interaction indicate that a higher subsidiary-only country share is associated with a slightly larger impact of regulatory tightenings on bank capitalization for higher HHI banks. However, this result is not statistically significant.

We next investigate business model factors. Concretely, regulatory actions might bite differently depending on the type of assets banks hold on their balance sheet. For example, a loan-to-value cap will affect loan business strongly, while a local currency reserve requirement will affect the cost of holding foreign government bonds. Similarly, certain types of assets or business may be harder to move to affiliates abroad. That is, the business model can both affect the *need* and the *ability* of banks to circumvent prudential regulation. To investigate this, we again include the share of tradable assets on the balance sheet in columns (5) and (6) of Table 2.4.2. However, in contrast to the economic shock analysis, the interaction coefficients are not significant.

Finally, we look at locational factors. The choice of host locations is likely an important determinant of the ease with which BHCs can circumvent regulatory actions. Moreover, the extent to which a bank needs to avoid regulation in the first place is likely to depend on the stringency with which regulatory actions are enforced. To analyze this, columns (5) and (6) include an indicator aimed at capturing the quality of the regulatory environment: $LowRegQuality_{it}$ is an average of two dummies each equal to 1 if the headquarter country, respectively the affiliate-weighted host country average, is below the 25^{th} percentile in regulatory quality, as measured by the World Bank. The triple interaction with this term is negative and significant. The results clearly indicate that in the presence of low regulatory quality, geographic complexity is less important in avoiding the effect of regulatory tightenings. A low quality regulatory environment already makes regulation less effective (see the double interaction of regulatory quality

[29] The exceptions are securities/assets with country-time fixed effects, and size (log assets) without country-time fixed effects (with size not being significant).

and $Pru.Reg$), so there is less scope for geographic complexity to play a role. This result is robust to the more demanding country-time fixed effects specification with only a slight decrease in coefficient size and statistical significance.

Table 2.4.2: Prudential Policy Changes, Geographic Complexity and Bank Capitalization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI_{it-1}	-0.0203	0.0127	0.0373	-0.00593	-0.0432	-0.0239	0.00181	0.00443
	(0.0320)	(0.0273)	(0.0539)	(0.0461)	(0.0373)	(0.0223)	(0.0405)	(0.0320)
Pru. Reg._{it-1}	-0.785*	-0.768**	-0.424	0.938	-0.650**	-0.688**	-2.510***	-1.754**
	(0.427)	(0.376)	(1.790)	(1.232)	(0.320)	(0.262)	(0.821)	(0.734)
$\text{HHI}_{it-1} \times$ Pru. Reg._{it-1}	0.00959**	0.00590*	0.00759	-0.0138	0.00793**	0.00715***	0.0271***	0.0204**
	(0.00475)	(0.00310)	(0.0213)	(0.0134)	(0.00392)	(0.00269)	(0.00991)	(0.00915)
$\text{SubCountryShare}_{it}$			12.40	-3.935				
			(9.261)	(7.665)				
$\text{HHI}_{it-1} \times \text{SubCountryShare}_{it}$			-0.117	0.0599				
			(0.112)	(0.0926)				
Pru. $\text{Reg.}_{it-1} \times \text{SubCountryShare}_{it}$			-0.752	-3.933				
			(4.468)	(2.817)				
$\text{HHI}_{it-1} \times$ Pru. $\text{Reg.}_{it-1} \times \text{SubCountryShare}_{it}$			0.00290	0.0480				
			(0.0549)	(0.0358)				
$\text{TradingAsssets}_{it-1}$					-41.48**	-7.277		
					(17.70)	(19.64)		
$\text{HHI}_{it-1} \times \text{TradingAsssets}_{it-1}$					0.467**	0.169		
					(0.225)	(0.224)		
Pru. $\text{Reg.}_{it-1} \times \text{TradingAsssets}_{it-1}$					4.593	15.79		
					(8.618)	(10.01)		
$\text{HHI}_{it-1} \times$ Pru. $\text{Reg.}_{it-1} \times \text{TradingAsssets}_{it-1}$					-0.0688	-0.143		
					(0.101)	(0.118)		
Low Reg. Quality_{it}							4.512	-2.123
							(4.817)	(3.353)
$\text{HHI}_{it-1} \times$ Low Reg. Quality_{it}							-0.0456	0.0251
							(0.0536)	(0.0383)
Pru. $\text{Reg.}_{it-1} \times$ Low Reg. Quality_{it}							4.148***	2.304
							(1.521)	(1.448)
$\text{HHI}_{it-1} \times$ Pru. $\text{Reg.}_{it-1} \times$ Low Reg. Quality_{it}							-0.0426**	-0.0316*
							(0.0184)	(0.0168)
Observations	616	563	616	563	420	384	616	563
R^2	0.778	0.910	0.782	0.911	0.828	0.928	0.783	0.911
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	No	Yes	No	Yes	No	Yes	No
CountryTimeFE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks	84	79	84	79	76	71	84	79

Notes: The dependent variable is bank risk, measured as 1 minus the regulatory Tier 1 capital ratio (higher values indicate higher risk). Sample consists of annual data from 2008 to 2016. HHI is the geographic Herfindahl-Hirschman index for the bank's foreign affiliates. Overall Pru. Reg. captures changes in prudential policies in the year, where a tightening of one policy is a +1, a loosening is a -1, in both headquarter and host countries. 50% weight is given to headquarter and host country policy changes, and host country changes is a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates. SubCountryShare is the share of countries that a bank only has access to through subsidiaries. TradingAssets is the share of tradable assets in total assets. Low Reg. Quality is the average of two dummies equal to 1 if the headquarter country, respectively the affiliate-weighted average of the host countries, is below the 25th percentile in regulatory quality, as measured by the World Bank. All control variables (Size, Loans, ROA, loan loss reserves (LLR), Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. LLR are normalized by lagged total loans. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Our results indicate that geographic complexity helps international banks avoid the impact of prudential regulation on their risk-weighted capitalization. This effect depends strongly on the regulatory quality with which the prudential policies in the home and host countries are enforced (locational factors). The importance of the share of subsidiary-only countries (organizational factors) and the share of tradable assets on the balance sheet (business model factors) is less pronounced.

To further understand the channels of regulatory circumvention suggested by the evidence in Table 2.4.2, we examine the heterogeneity of the baseline effect along the dimensions of regulation types and location. We split our prudential measures into the following groups: capital regulation, reserve regulation, and exposure regulation. The first group contains measures such as general requirements of capitalization or provisioning levels. The second group consists of measures directly targeting the reserves banks need to hold in local or foreign currency. The third group is the broadest and contains measures that aim at reducing excessive risk-taking by banks, such as concentration limits, interbank exposure limits or loan-to-value caps. Moreover, we split the measures depending on whether they are applied in the country of headquarters or in an affiliate-weighted average of the host countries.

Each of these types of regulation, though targeting different things, can impact bank capitalization. Capital requirements do so directly. Reserve requirements may affect capitalization because they force banks to hold more of their assets in cash or other liquid assets bearing zero risk weight. This replaces the marginal lending which may have gone to riskier borrowers carrying a larger risk weight. Since these regulations are typically applied to deposits in a location rather than to the consolidated balance sheet, geographically complex banks may get around this by shifting activity (e.g. risky lending) to affiliates in other locations. Exposure limits can affect capitalization because these measures are often expressed as a percentage of capital (e.g. single-sector exposures should not exceed X% of Tier 1 capital). Thus, a tightening of these measures forces banks to raise more capital if they wish to maintain their exposures. A geographically complex bank can increase exposure via foreign affiliates rather than raise capital.

Table 2.4.3 presents the results of this split. We first note that many capital regulations were implemented around the same time, due to global regulatory initiatives related to Basel III, so much of their direct impact is absorbed by time fixed effects and HHI plays no role in providing heterogeneity (column (1)). The significant effect of tightening exposure (column (2)) or reserve (column (3)) regulations in the headquarter country, however, can be weaker for more geographically complex BHCs, with exposure regulation dominating when included in the same regression (column (4)). When looking at host country regulation, we find that high HHI only helps in weakening the effect of reserve requirements.[30]

Table 2.4.3: Prudential policy changes, by subgroup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI_{it-1}	-0.00807	-0.00896	-0.000852	-0.00330	-0.0189	-0.0228	-0.0269	-0.0263
	(0.0278)	(0.0285)	(0.0279)	(0.0273)	(0.0308)	(0.0328)	(0.0332)	(0.0328)
HQ Cap. Reg._{it-1}	0.586			0.663				
	(1.021)			(0.974)				
$\text{HHI}_{it-1} \times$ HQ Cap. Reg._{it-1}	-0.00899			-0.0101				
	(0.0121)			(0.0116)				
HQ Expos. Reg._{it-1}		-1.154***		-2.078***				
		(0.352)		(0.572)				
$\text{HHI}_{it-1} \times$ HQ Expos. Reg._{it-1}		0.0136***		0.0218***				
		(0.00431)		(0.00714)				
HQ Res. Req._{it-1}			-0.358**	0.381				
			(0.139)	(0.247)				
$\text{HHI}_{it-1} \times$ HQ Res. Req._{it-1}			0.00543***	-0.00215				
			(0.00159)	(0.00302)				
Host Cap. Reg._{it-1}					-1.014			-0.965
					(0.689)			(0.724)
$\text{HHI}_{it-1} \times$ Host Cap. Reg._{it-1}					0.0120			0.0119
					(0.00970)			(0.0100)
Host Expos. Reg._{it-1}						-1.629*		1.153
						(0.838)		(1.074)
$\text{HHI}_{it-1} \times$ Host Expos. Reg._{it-1}						0.0202		-0.0121
						(0.0128)		(0.0158)
Host Res. Req._{it-1}							-2.507**	-3.200**
							(0.987)	(1.288)
$\text{HHI}_{it-1} \times$ Host Res. Req._{it-1}							0.0288**	0.0357**
							(0.0124)	(0.0153)
Observations	633	633	633	633	616	616	616	616
R^2	0.771	0.771	0.771	0.775	0.778	0.778	0.779	0.780
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks	86	86	86	86	84	84	84	84

Notes: The dependent variable is bank risk, measured as 1 minus the regulatory Tier 1 capital ratio (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. HHI is the bank's geographic Herfindahl-Hirschman index. $Cap.\ Reg$ consists of sector-specific capital buffer and other capital regulation actions. $Expos.\ reg.$ includes concentration ratio, interbank exposure and loan-to-value measures. $Res.\ Req$ includes foreign and local currency reserve requirement actions. Policy actions are measured as +1 for tightening and -1 for loosening. HQ indicates prudential policy actions in the bank's home country, $Host$ indicates an affiliate weighted average of actions in host countries where the bank has affiliates. All bank control variables (Size, Loans, ROA, loan loss reserves (LLR), Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets, LLR are normalized by lagged loans. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Taken together, these results point to two important insights. First, capital regulation cannot easily be avoided by being more geographically complex. These measures are often applied to the consolidated bank's balance sheet, and are more harmonized across

[30] The robustness check with $country \times time$ fixed effects can be found in Appendix 2.B. Results for exposure regulation and reserve requirements in home countries survive this more demanding specification.

countries. Second, reserve and exposure regulation may benefit from better coordination across borders to be more effective in fostering financial stability. These measures have a beneficial effect on bank risk by reducing risk-based leverage for banks without foreign affiliates, as the significant non-interacted coefficients in Table 2.4.3 show. But greater geographical complexity provides opportunities to undo some of that effect, advantaging larger international banks over domestic ones with respect to these regulations.

Contrary to the diversification value provided by geographic complexity for local economic shocks, the effect uncovered in this section is detrimental from a financial stability perspective, as it weakens the positive effects of regulation. Our results link bank geographic complexity with a weakened impact of regulation on bank risk in a global sample. The cross-country nature of our dataset allows us to control for any observed and unobserved factors varying at the country level over time which may otherwise contaminate the results.

Appendix 2.C presents further evidence consistent with the findings in this section using a global regulatory reform, namely the implementation of the GSIB framework. Using a difference-in-differences approach with inverse probability weighting, this analysis shows that GSIB designation reduced idiosyncratic bank risk, but that this effect is weakened for more geographically complex GSIBs.

2.5 Conclusion

This paper constructs a unique dataset of bank geographic complexity based on the BIS Banking List. We build a Herfindahl-Hirschman indicator which conceptually accounts for the bank's number of international banking affiliates, its geographic reach (number of host countries) and the concentration of affiliates across its host countries. This indicator, constructed for 96 of the largest bank holding companies in the world headquartered in 22 different countries, provides information different from and complementary to that captured by other measures of complexity, including the BCBS measures of complexity (used in assessing G-SIBs, incorporating factors like size and opaque assets) and geographic spread measures based on lending.

We find robust evidence that bank geographic complexity can help cushion the negative effects of local economic shocks. These findings are in line with the literature on the role of diversification as a moderator of bank risk, as a more geographically complex bank is also a more diversified bank. The importance of bank geographic complexity in this regard depends on organizational, business model, and locational factors, as we find three dampening forces to the diversification effect: i) a higher share of countries that banks have access to only through subsidiaries, ii) a higher share of tradable assets on their balance sheet, and iii) a higher synchronicity of host and home countries' business cycles.

Bank geographic complexity, however, has a Janus face. This becomes evident when assessing the role such complexity plays when dealing with changes in regulation. In particular, a wider geographic reach can also be a vehicle allowing banks to alter the effects of regulation on their balance sheet, potentially increasing risk. We find robust evidence that bank geographic complexity can weaken the mitigating effect that tighter prudential regulation has on bank risk. This finding exhibits meaningful heterogeneity stemming from the quality of regulatory enforcement such that geographic complexity is less important if regulation is not stringently enforced. Reserve requirements and exposure regulations drive the results of regulatory circumvention. Capital regulation, which is more encompassing and has been applied largely in a globally coordinated manner, is less prone to be circumvented through geographic complexity. Our results provide valuable information on the effectiveness of prudential regulation when applied to internationally active and geographically complex banks and emphasize the importance of and need for better (global) coordination of prudential policies.

Appendix

2.A Additional summary statistics, definitions and sources

Table 2.A.1: Variable definitions and sources – part 1

Variable	Definition	Source
Bank balance sheet, complexity and market variables		
HHI	Geographic Herfindahl-Hirschman index (see Equation 2.1)	BIS
$z-score$	1/log(z-score); z-score = (ROA + Equity/Assets)/sd(ROA); standard deviation computed over 40 rolling quarters	Fitch
$bank\_cap$	1 - regulatory Tier1 capital ratio	Fitch
$Size$	Logarithm of total assets	Fitch
ROA	Average return on assets	Fitch
LLR	Loan loss reserves scaled by total loans	Fitch
$Loans$	Loans scaled by total assets	Fitch
$Securities$	Securities scaled by total assets	Fitch
$Deposits$	Deposits scaled by total assets	Fitch
$TradingAssets$	Tradable assets scaled by total assets	Fitch
CDS $spread,$ $idiosyncratic$	Orthogonalization between the first principal component of the respective series across all banks and the original series	Markit, Datastream, Authors' calculation
CDS $spread,$ $systematic$	Fitted values from regressing the original series onto the systematic component	Markit, Datastream, Authors' calculation
$SRISK$	Capital shortfall of a firm conditional on a severe market decline	NYU Stern V-lab

Table 2.A.2: Variable definitions and sources – part 2

Variable	**Definition**	**Source**
Country-bank variables		
$LowRegQuality$	Average of two dummies; dummy =1 if home country, respectively affiliated-weighted average of host countries, is in the lower 25^{th} percentile of the regulatory quality index	World Bank
$SubCountryShare$	Share of host countries the bank only has access to through subsidiaries	BIS
$PruReg$	Average of headquarter and host country prudential regulation (using the 9 categories from the macroprudential regulation dataset). 50% weight is given to headquarter and host country policy changes, with the latter being a weighted average (by number of affiliates) of the policy changes enacted in the countries in which the bank has foreign affiliates	Cerutti et al. [2017], BIS
$Cap.\ Reg$; $Expos.\ Reg$; $Res.\ Reg$ ($HQ/Host$)	Respectively Capital Regulation (sector-specific capital buffer and other capital regulation actions); Exposure Regulation (concentration ratio, interbank exposure and loan-to-value measures); Reserve Requirements (foreign and local currency reserve requirement actions). Computed as +1 for each tightening and -1 for loosening, for the home country (HQ) and the affiliate-weighted average of host countries ($Host$)	Cerutti et al. [2017], BIS
$GDP\ growth$	Real GDP growth	IMF
$GDP\ corr.$	Weighted bilateral correlations of the real GDP growth of the headquarter country with all the host countries, with weights given by the number of affiliates in the different host countries	IMF, BIS
$GDP\ Shock$	Realized real GDP growth minus forecast for the same year	IMF (actual), OECD (forecast)
Other		
$GSIB$	Dummy = 1 if the bank was designated as a GSIB in 2011	BCBS
$Post$	Dummy = 1 if year is 2011 or later	Author's calculation

Table 2.A.3: Bank variables - sample-wide descriptives

	Size	ROA	LLR	Loans	Sec	Dep	Z-score	Cap	Trad.Ass.
Mean	13.32	0.78	1.59	49.97	32.72	48.51	0.41	0.88	7.64
Median	13.29	0.73	1.00	51.35	29.35	49.15	0.37	0.88	5.73
Std	0.84	0.86	1.73	17.86	16.37	18.77	0.15	0.03	7.64
Min	11.62	-4.19	0.00	0.99	2.41	4.23	0.24	0.71	0.01
Max	15.07	5.65	9.62	88.39	87.17	86.93	1.51	0.95	35.78
No of Obs	768	768	752	764	768	756	705	728	547

Notes: *Size* is measured as the logarithm of total assets. *ROA* is the return on assets, expressed as percentage. *Loans*, securities (*Sec*) and deposits (*Dep*) are all expressed as a percentage of total assets. *LLR* stands for loan loss reserves over total loans multiplied by 100. *Z-score* stands for 1/log(z-score). *Cap* stands for 1 - Tier1 Capital Ratio. *Trad.Ass.* stands for trade-able assets as a percentage of total assets.

Table 2.A.4: Additional variables - sample-wide descriptives

	GDP Shock	GDP Growth	GDP corr.	SubCountryShare	PruReg	LowRegQuality
Mean	-0.00	3.27	0.60	0.38	0.34	0.24
Median	0.00	2.71	0.72	0.33	0.25	0
Std	0.13	3.35	0.31	0.16	0.79	0.29
Min	-0.74	-5.10	-0.23	0.13	-2.5	0
Max	0.55	14.21	0.94	0.86	3.15	1

Notes: Definitions as in Tables 2.A.1 and 2.A.2.

Figure 2.A.1 presents a stylised description of the list data for a given year in its raw format and the transformations we apply to it. Every observation comprises a banking entity reporting from a given country within the list of countries that report to the BIS locational banking statistics. In the stylised example we have three reporting countries (X, Y and Z) and three BHCs indexed 1, 2 and 3. BHC1 is headquartered in country X and has three domestic entities reporting from that country. It also has presence in the other two countries via a combination of branches, subsidiaries, and other bank types. BHC2 is headquartered in country Y, but also has branches reporting from country X and subsidiaries reporting from country Z. Finally BHC3 is headquartered in country Z, but has one and two subsidiaries reporting in countries X and Y respectively. We first reorganise the list around BHCs, as indicated in the middle part of Figure 2.A.1. Then, based on this, we compute complexity indicators at the BHC(-year) level as shown in the rightmost part of Figure 2.A.1.[31]

In the banking list, we can identify 5 types of affiliates: domestic affiliates, foreign subsidiaries, foreign branches, consortium banks (only located in Japan), and non-bank affiliates (only those located in the United States). Given the limited number of consortium banks and non-banks in the dataset, we restrict our analysis to either the total count available or the count of foreign subsidiaries and branches. Furthermore, we do not consider non-bank affiliates in our regression analysis.

Figure 2.A.2 provides a bird's eye view of the network of international affiliates for the group of 96 BHCs in our study, as of end-2016. Node size indicates the number of incoming and outgoing connections. Black nodes denote jurisdictions in which one or more of the BHCs in our sample are headquartered, whereas red nodes denote countries where only affiliates of BHCs headquartered in the "black node" jurisdictions are

[31] In practice the construction of the international footprint of BHCs is not as automatic nor as straightforward as Figure 2.A.1 implies. A substantial amount of manual work goes into matching each of the bank entities in the banking list in each year into the BHCs they are a part of.

Figure 2.A.1: From raw banking list to holding company-level indicators

Stylised version of list in raw form

Reporting country	*Bank name*	*Bank type*	*Parent country*	*Parent name*	*...*
X	AA	D	-	BHC1	
X	AB	B	Y	BHC2	
X	AC	B	Y	BHC2	
X	AD	S	Z	BHC3	
X	AE	D	-	BHC1	
X	AF	B	Y	BHC2	
X	AG	S	Z	BHC3	
X	AH	D	-	BHC1	
X	AI	D	-	AI	
Y	BA	B	X	BHC1	
Y	BB	S	X	BHC1	
Y	BC	O	X	BHC1	
Y	BD	D	-	BHC2	
Y	BE	D	-	BE	
Y	BF	D	-	BF	
Y	BG	S	Z	BHC3	
Z	CA	D	-	CA	
Z	CB	D	-	CB	
Z	CC	D	-	BHC3	
Z	CD	D	-	BHC3	
Z	CE	O	X	BHC1	
Z	CF	S	Y	BHC2	
Z	CG	B	X	BHC1	
Z	CH	S	Y	BHC2	

Stylised version of tranformed list

BHC name	*HQ country*	*Reporting country*	*Bank Type*	*...*
BHC1	X	X	D	
BHC1	X	X	D	
BHC1	X	X	D	
BHC1	X	Y	B	
BHC1	X	Y	S	
BHC1	X	Y	O	
BHC1	X	Z	B	
BHC1	X	Z	O	
BHC2	Y	X	B	
BHC2	Y	X	B	
BHC2	Y	X	B	
BHC2	Y	Y	D	
BHC2	Y	Z	S	
BHC2	Y	Z	S	
BHC3	Z	X	S	
BHC3	Z	X	S	
BHC3	Z	Y	S	
BHC3	Z	Z	D	
BHC3	Z	Z	D	

Data ready for merging

BHC name	*Complexity indicators*			
	#1	*#2*	*#3*	*#...*
BHC1	...	...	...	...
BHC2	...	...	...	...
BHC3	...	...	...	...

located. Links between countries denote the existence of affiliates. A significant amount of the connections link North America and Europe, and these two with Asia.

Figure 2.A.2: The global network of foreign affiliates (as of end-2016)

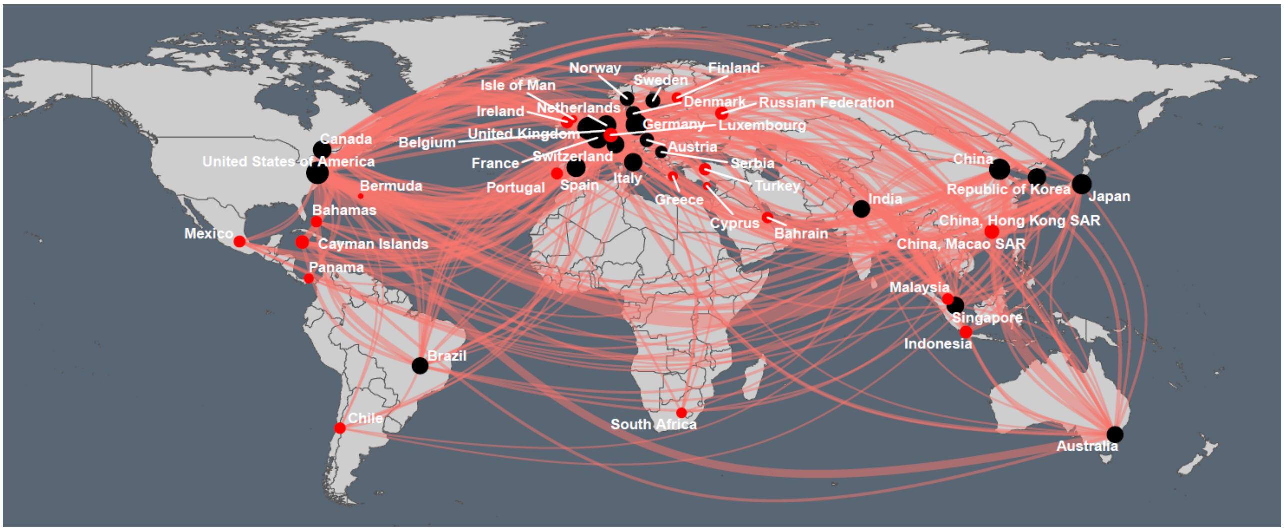
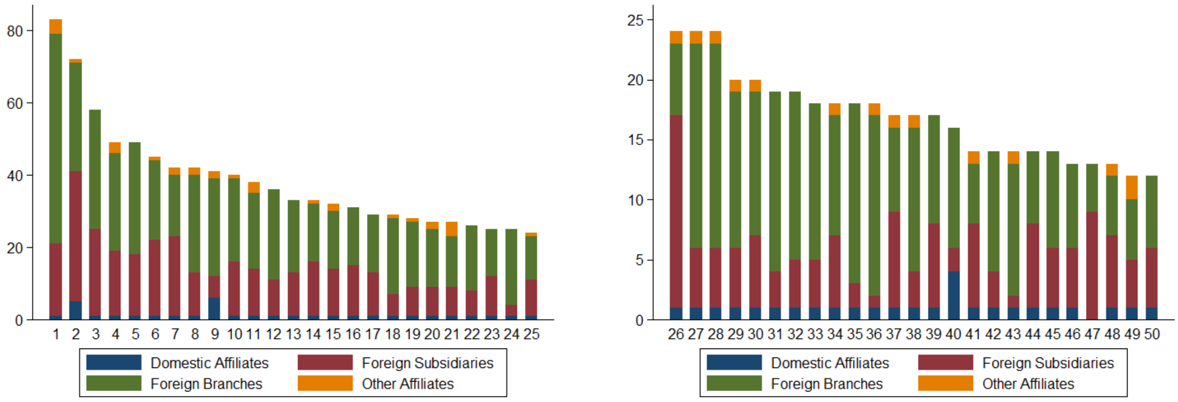


Figure 2.A.3 plots the affiliate structure of the BHCs, sorted by the total number of affiliates. The BHC with the most internationally active affiliates has over 80 affiliates, followed by about 70 for the second and about 60 for the third. After that, there is a more gradual decline, but with variation in the composition of the affiliates. The largest segment of affiliates for most BHCs is foreign branches, though a few have more foreign subsidiaries than branches.

Figure 2.A.3: Affiliate structure, by rank of total affiliates



a) Rank 1-25

b) Rank 26-50

Notes: Rank based on affiliates in 2016. Affiliates include internationally active banking entities across BIS reporting countries. Other affiliates include consortium banks in Japan and non-banks in US.

Figure 2.A.4: Correlation matrix of complexity related indicators

	HHI	DS Indicator	Size	Loans/Assets	Securities/Assets	Deposits/Assets	GSIB complexity
HHI	1	-0.03	0.19	-0.03	0.01	-0.1	0.06
DS Indicator	0.51	1	0.11	-0.06	0.02	-0.03	0.04
Size	0.43	0.47	1	-0.21	0.11	-0.25	0.18
Loans/Assets	-0.32	-0.2	-0.32	1	-0.46	0.26	-0.14
Securities/Assets	0.25	0.26	0.35	-0.85	1	-0.26	0.17
Deposits/Assets	-0.21	-0.33	-0.14	0.34	-0.38	1	-0.18
GSIB complexity	0.35	0.02	0.59	-0.53	0.56	-0.32	1

Notes: The lower left triangle reflects raw bilateral correlations by indicator pairs. The upper right triangle reflects bilateral correlations after controlling for bank fixed effects.

2.B Robustness with $country \times time$ fixed effects

Table 2.B.1: Prudential policy changes, by subgroup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HHI_{it-1}	0.0186	0.0161	0.0164	0.0172	0.0154	0.0124	0.0134	0.0141
	(0.0244)	(0.0248)	(0.0249)	(0.0248)	(0.0270)	(0.0275)	(0.0278)	(0.0275)
HHI_{it-1} × HQ Cap. Reg.$_{\cdot it-1}$	0.00824			0.00735				
	(0.00839)			(0.00814)				
HHI_{it-1} × HQ Expos. Reg.$_{\cdot it-1}$		0.00816**		0.0109*				
		(0.00396)		(0.00637)				
HHI_{it-1} × HQ Res. Req.$_{\cdot it-1}$			0.00247	-0.00186				
			(0.00151)	(0.00254)				
Host Cap. Reg.$_{\cdot it-1}$					-0.924			-0.730
					(0.567)			(0.577)
HHI_{it-1} × Host Cap. Reg.$_{\cdot it-1}$					0.00809			0.00534
					(0.00908)			(0.00898)
Host Expos. Reg.$_{\cdot it-1}$						-1.162		-0.504
						(0.943)		(1.452)
HHI_{it-1} × Host Expos. Reg.$_{\cdot it-1}$						0.0167		0.0132
						(0.0150)		(0.0205)
Host Res. Req.$_{\cdot it-1}$							-0.504	-0.423
							(0.769)	(1.358)
HHI_{it-1} × Host Res. Req.$_{\cdot it-1}$							0.00321	-0.00130
							(0.00993)	(0.0151)
Observations	580	580	580	580	563	563	563	563
R^2	0.907	0.907	0.907	0.907	0.910	0.910	0.910	0.911
BankFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryTimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banks	81	81	81	81	79	79	79	79

Notes: The dependent variable is bank risk, measured as 1 minus the regulatory Tier 1 capital ratio (higher values indicate higher risk). The sample consists of annual data from 2008 to 2016. HHI is the bank's geographic Herfindahl-Hirschman index. $Cap.\ Reg$ consists of sector-specific capital buffer and other capital regulation actions. $Expos.\ reg.$ includes concentration ratio, interbank exposure and loan-to-value measures. $Res.\ Req$ includes foreign and local currency reserve requirement actions. Policy actions are measured as +1 for tightening and -1 for loosening. HQ indicates prudential policy actions in the bank's home country, $Host$ indicates an affiliate weighted average of actions in host countries where the bank has affiliates. All bank control variables (Size, Loans, ROA, loan loss reserves (LLR), Securities, Deposits) are lagged by one period. Loans, Securities and Deposits controls are all normalized by lagged assets. LLR are normalized by lagged total loans. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

2.C Complexity and global regulation

In this appendix we expand our scope to global regulation to provide further evidence on how bank geographic complexity can weaken the positive effect of regulation on bank risk. In particular, we investigate the implementation of the GSIB framework.

Since 2011, the BCBS and the Financial Stability Board compile and publish a yearly list of the most systemically relevant banks worldwide, which are subject to additional regulatory scrutiny and additional capital requirements – the so-called GSIB buffer. The first list was published in 2011, without additional information. In 2012 the list was updated and further information on GSIB bucket allocation[32] by bank was disclosed. Finally, in 2013 the list was updated and the methodology for bucket allocation was made fully transparent (BCBS [2013]). Since the first list of banks was already disclosed in 2011, we take this year as the implementation date.

GSIB assignment is not random, so its use presents some endogeneity challenges for identification. To address this, we employ an inverse probability weighting (IPW) approach (Hirano et al. [2003a]). This method builds upon the idea of "exogenizing" the assignment by applying weights to the sample which are inversely related to the likelihood of being designated as a GSIB a priori. A lower weight is assigned to treated banks which were very likely to be treated and to untreated banks which were very likely to be untreated. Conversely, a higher weight is assigned to banks for which the treatment status was hard to predict, given their pre-GSIB situation. We are further advantaged by the fact that GSIB assignment involves a judgement call in addition to the raw score, so receiving a score near the (ex-post) threshold would still carry some uncertainty around GSIB designation.

To formalize this idea, consider $\widehat{Prob}_i$ as the probability that bank i at the end of 2010 is classified as a GSIB in the first list in 2011. We obtain these values by fitting a logit model of the treatment dummy onto a set of balance sheet indicators, which are as close as possible to the measures actually used in the GSIB assessment exercise.[33] We then run a regression of the form:

$$\begin{aligned}\tilde{Risk}_{i,t} = \alpha_t + \epsilon_i + \beta_1 \tilde{Treatment}_i \times \tilde{Post}_t + \beta_2 \tilde{Post}_t \times \tilde{Complexity}_i \\ + \beta_5 \tilde{Treatment}_i \times \tilde{Post}_t \times \tilde{Complexity}_{i,t-1} + \tilde{Post}_t \times \tilde{\mathbf{X}}_i \Gamma + \tilde{\nu}_{i,t},\end{aligned} \tag{2.5}$$

[32]The GSIBs are classified into separate buckets, requiring different levels of additional capital.
[33]The actual GSIB scores for 2010 are not available to construct these weights.

where $\tilde{Z}_{it} = \frac{Z_{it}}{IPW_i}$ with $IPW_i = \frac{1}{\widehat{Prob_i}}$ for treated and $IPW_i = \frac{1}{1-\widehat{Prob_i}}$ for non-treated. We take the pre-treatment average of complexity and of our controls to match the difference-in-differences specification.

We now focus on market-based instead of balance sheet measures as our benchmark left-hand side variables of interest. This is because the GSIB assessment is a large, structural and new framework with long-lasting effects on affected banks' business models, as well as on the market structure as a whole. This is likely to be reflected in the forward-looking market assessment of the banks. As an indicator of realized risk, the z-score is less likely to be affected since, for instance, the GSIB designation will not immediately affect banks' business over and above the additional regulatory capital buffer, which was phased in slowly.

We use three different left-hand side variables capturing market based measures of risk, namely systemic risk, idiosyncratic risk and systematic risk. Systemic risk indicators aim to capture the contribution of individual financial institutions to the likelihood of large system-wide financial disruptions. Systematic risk indicators capture market risk that cannot be diversified away. Idiosyncratic risk, in turn, captures the part of bank risk that is uncorrelated to the systematic component. We use the SRISK systemic risk measure to capture a bank's contribution to systemic risk [Brownlees and Engle, 2016]; it measures the capital shortfall of a firm conditional on a severe market decline, and is a function of its size, leverage and risk. We compute idiosyncratic risk for CDS spreads by calculating the first principal component across all banks and orthogonalizing the original series to this principal component, thereby purging it from market-wide systematic effects. Finally, we compute systematic risk based on the fitted values from regressing the original series on the systematic component.[34]

The first three columns of Table 2.C.1 show the results of the IPW approach applied to Equation 3.4. Column (1) shows that systemic risk was not impacted by the GSIB designation on average, nor was there heterogeneity along the geographic complexity dimension. Column (2), however, indicates that the GSIB designation reduced idiosyncratic bank risk (i.e. the idiosyncratic component of CDS spreads went down). However, the more geographically complex a bank is, the weaker this effect – up until

[34] We prefer to use the components of CDS spreads over the components of stock returns as measures of risk, since a CDS contract specifically captures default risk, while a stock return captures a more complex economic outlook. However, results for risk measures extracted from stock returns are consistent with those from CDS spreads. For balance sheet-based measures of risk such as leverage and the z-score we do not find any significant effect. Results are available upon request.

the point where the most complex GSIBs actually saw an increase in their market-based risk assessment. We do not observe any significant effect in the systematic component of banks' CDS.

Table 2.C.1: GSIB implementation, geographic complexity and bank risk

	(1) SRISK	(2) Idio. Risk	(3) Sys. Risk	(4) SRISK	(5) Idio. Risk	(6) Sys. Risk
$GSIB_i \times Post_t$	-25552.4	-232.4***	6.681	-296167.7*	-381.2***	17.03
	(133913.7)	(69.93)	(15.88)	(158486.1)	(110.1)	(17.44)
$Post_t \times HHI_i$	276.4	0.572	0.00874	618.4	0.537	-0.0504
	(340.0)	(0.708)	(0.0842)	(511.5)	(0.667)	(0.0883)
$GSIB_i \times Post_t \times HHI_i$	406.3	2.654***	-0.103	3428.7*	4.535***	-0.187
	(1523.2)	(0.859)	(0.179)	(1814.7)	(1.121)	(0.179)
Observations	431	477	477	347	405	405
R^2	0.865	0.118	0.944	0.943	0.695	0.973
BankFE	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	No	No	No
CountryTimeFE	No	No	No	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Banks	49	53	53	39	45	45

Notes: Higher values in the left-hand side variable indicate higher risk. The sample consists of annual data from 2008 to 2016. GSIB is a dummy variable equal to 1 (for all periods) if the bank was designated as a GSIB in 2011, and 0 otherwise. Post is a dumy equal to 1 for 2011-2016, and 0 otherwise. HHI is the bank's geographic Herfindahl-Hirschman index, pre-period average. All bank control variables (Size, Loans, ROA, Securities, Deposits) are pre-period averages interacted with the post dummy. Loans, Securities and Deposits controls are all normalized by assets. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

Differences in the macroeconomic, regulatory or financial environment as well as structural differences in banking systems across countries could potentially be biasing results. In columns (4) to (6) we present the same set of regressions as in the first three columns but controlling for country-time fixed effects, in order to absorb such time-specific sources of variation for the different countries where banks in our sample are headquartered.

Results on the impact of GSIB designation are robust to this more demanding empirical specification. Systemic risk also appears to follow the same pattern (regulation decreases risk, complexity attenuates the effect). Altogether, these results provide corroborating evidence to that of Section 2.4.2 that geographic complexity weakens the impact of regulation on measured risk, for both local and global regulatory efforts.

Chapter 3

Kicking the can down the road: government interventions in the European banking sector

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3.1 Introduction

Governments in an economy whose banking sector exhibits systemic distress have two types of interventions at their hand: system-wide measures affecting the banking sector as a whole and single-bank measures aimed at banks most in need (Farhi and Tirole [2012]). In most cases, system-wide measures are performed by monetary authorities in the form of conventional policy (i.e. lowering interest rates) and/or unconventional policy (e.g. larger-scale asset purchase programs, such as TARP). In contrast, single-bank measures are usually conducted by the fiscal authority with either immediate incidence of fiscal costs or using government guarantees. Following Pazarbasioglu et al. [2011], bank-level measures in recent banking crises can be grouped into three categories, which are usually implemented sequentially as a crisis worsens: i) guarantees, ii) capital injections, iii) asset restructuring/resolution. While step i) implies a short-run fiscal cost close to 0, steps ii) and iii) typically require governments to run a higher fiscal deficit, which has to be financed with higher debt or taxes. Therefore, fiscally constrained governments may deploy guarantees and/or engage in some form of forbearance (e.g. relax capital requirements or and asset quality recognition norms), and, in particular, decide not to implement step ii).[1]

We investigate these government interventions choices in the context of the Global Financial Crisis (GFC) and its impact on the European banking sector. While banks across all European countries were in distress, there was no centralized scheme at the European level to provide aid for individual banks. Therefore, bailout decisions were subject to the discretion and the fiscal constraints of the national governments.

Our analysis of government interventions builds on a novel, hand-collected dataset of all aid measures granted to eurozone banks during the 2007 to 2009 period. A key measure of fiscal capacity is the country's ratio of government revenues to GDP (e.g. Dincecco and Prado [2012]). Higher revenues increase the capacity to recapitalize banks in distress (Stavrakeva [2020]). Another widely used measure for fiscal strength is the total debt stock as a percentage of GDP (e.g. Demirgüç-Kunt and Huizinga [2013]). A high government debt level can imply a tight budget, especially if debt is short term and has to be refinanced in the near future. We thus also include the proportion of maturing debt of a country as a relevant fiscal metric. In addition, we employ the current account surplus/deficit as a potential determinant as fiscal constraints are likely to become more binding when a country borrows from abroad.

We use a bank-level hazard model to analyze the time until the first government intervention for a distressed bank. We show that banks located in countries with lower fiscal capacity were at least as likely to receive any form of government support as banks located in countries with stronger public finances.[2] However, consistent with the hypothesis that capital injections are costly in the sense that they tighten the government budget constraint in the short run, fiscally constrained governments delayed or suspended capital injections more than fiscally stronger countries. The effect is economically significant. For instance, the likelihood that a bank is recapitalized increases by about 30% when the sovereign's revenues-to-GDP ratio increases by 1 percentage point (p.p.). The result is robust across different measures of fiscal capacity and holds after controlling for an array of bank-level, banking sector-level, and macro-level vari-

[1] According to Pazarbasioglu et al. [2011], step iii) is a rare event even in crisis times.

[2] Duration analysis is widely used to analyze bank failures and/or government interventions in the banking sector (see, e.g. Lane et al. [1986]; Whalen et al. [1991]; Brown and Dinc [2005]; Brown and Dinç [2011]). In particular, it has been shown to be superior to single-period models for forecasting the occurrence of events such as bankruptcy (Shambaugh et al. [2012]).

ables, as well as political control variables, such as CAMEL type bank-level controls, too-many-to-fail effects (Acharya and Yorulmazer [2007]; Brown and Dinç [2011]), election cycles (Brown and Dinc [2005]), and other factors.

In a next step, we investigate portfolio and lending decisions of banks that remained undercapitalized at the end of 2009, i.e. after the GFC. A key identification challenge is that undercapitalization itself is endogenous and depends on both pre-crisis bank characteristics, i.e. banks' predisposition to require a bailout, and the ability and willingness of governments to bail out banks. To address this challenge, we use an econometric method developed by Hirano et al. [2003b], and used, among others, by Jordà and Taylor [2016], called "inverse probability weighting".

This method does not produce a classification as to which banks are undercapitalized but requires this information as an input. To that end, we classify a bank as undercapitalized if one of the following three conditions is met: (1) the Tier 1-capital ratio is below 8%, or, if this data is not available, (2) the equity-to-assets ratio is below 3% (the BCBS[3] leverage ratio requirement) or (3) the non-performing loans (NPL)-to-total-loans ratio is in the top 5% of all banks in our sample at the end of 2009.[4] We then regress this indicator variable of a bank being undercapitalized on a set of bank and country characteristics (and their interaction terms) that we found to be important determinants in our first test of whether or not a bank is recapitalized. Since this regression captures the factors that were on average important in determining banks' capitalization status in 2009, the difference between the prediction of the model and the actual outcome for a banking sector can be interpreted as the degree of the country's governmental discretion. For example, consider two banks that are similarly weak according to their bank-level characteristics, one located in Germany and the other one in Ireland, which both do not receive a bailout and end up being undercapitalized. Given the higher level of fiscal capacity, the degree of forbearance for the bank in Germany would be considered higher than the degree of forbearance for the bank in Ireland, where fiscal capacity was more likely the binding constraint.

Reweighting the sample with weights corresponding to the extent of governmental discretion implied by the bank's outcome then allows us to put the spotlight on those banks that were still undercapitalized because of forbearance. From a statistical point

[3]BCBS stands for Basel Committee on Banking Supervision.
[4]Our results are robust to alternative definitions of "undercapitalized banks".

of view, the weights allow us to reduce (or even eliminate) the bias from endogenous treatment assignment in the subsequent treatment effects models.[5]

Armed with these weights, we investigate the effect of being undercapitalized on bank-level outcomes during the period 2009 to 2012. Our second main result is that banks that were undercapitalized at the end of 2009 were more vulnerable or financially unstable. Over the next three years, undercapitalized banks lost further equity capital, reduced lending, but increased their loan loss provisions compared to their better-capitalized peers. Undercapitalized banks also increased their short-term borrowing from the European Central Bank (ECB) using its three-year Long-Term Refinancing Operation (LTRO) facility introduced in 2011. Undercapitalized banks did not, however, have a higher probability to default, likely because their liquidity was secured via ECB funding.

We then analyze individual lending decisions by banks using the intersection of loan-level data from the Thomson Reuter Dealscan and Bureau van Dijk's Amadeus database to identify both banks and firms. Using a regression framework similar to Khwaja and Mian [2008], which captures firm demand for loans using firm fixed effects, we find that undercapitalized banks reduced loan supply to non-financial firms, both for relationship borrowers (intensive margin) and for new borrowers (extensive margin). Investigating the effect on lending as a function of borrower risk, we find that undercapitalized banks significantly reduced their loan supply to risky firms relative to better-capitalized banks.

This is intuitive as riskier lending binds (regulatory) capital. Interestingly, however, we do not find evidence that undercapitalized banks reduced lending to risky relationship firms, suggesting an evergreening of loans to "zombie" firms. We test this hypothesis directly using the definition of "zombie" firms in Acharya et al. [2018]. This definition requires a low credit quality firm to be receiving subsidized credit, i.e., paying an interest rate below the average for highly rated borrowers of the same industry.

[5]This method has been used extensively in the recent literature: Angrist et al. [2018], Yim [2013], Jordà and Taylor [2016], Acemoglu et al. [2019], and Kuvshinov and Zimmermann [2019]. The reweighting with weights based on a prediction of the treatment status allows the bias from endogeneity of treatment assignment to be reduced. Taking the example of Kuvshinov and Zimmermann [2019], factors which were relevant ex ante as to whether a sovereign will default ("treatment"), e.g. lower economic growth, can also be relevant for the cost of the sovereign default ("treatment effect"). The weighting approach allows removal of the bias caused in the default cost estimation due to differences in GDP growth between defaulted and non-defaulted countries. The more (observable) factors one can control for, the more bias is removed and the more "exogenous" the treatment becomes. Obviously, missing variables or information affecting both treatment status and treatment effect can be a constraint for the method.

We find that undercapitalized banks increased the supply of credit to ″zombie″ firms while reducing lending to ″non-zombie″ firms, relative to better-capitalized banks. We also provide evidence that the ″zombie″ firms that are matched with banks that become undercapitalized in the lending market, perform worse than similar firms matched with better-capitalized banks.

Moreover, we investigate a behavior we call ″search-for-yield lending″. Within a risk class, and therefore within a regulatory risk weight and capital cost category, undercapitalized banks gamble for resurrection by seeking borrowers accepting a higher interest rate. That is, for the same cost, undercapitalized banks prefer the potential upside relative to the (within-rating category) risk more than better-capitalized banks do. We find strong evidence for such behavior in the intensive margin of lending of undercapitalized banks.[6]

Finally, we examine the composition of assets on undercapitalized banks' balance sheets. We observe that they shift a considerable part of their portfolio from real sector lending to government bonds during the period from 2009 to 2012. The average undercapitalized (better-capitalized) bank reduces (increases) its lending portfolio by 1 p.p. (2 p.p.) of total assets and increases (also increases) its security exposure by 5.5 p.p. (0.25 p.p.) of total assets. These heightened government bond purchases by undercapitalized banks happen particularly in the years 2011 and 2012 when several government bond yields had spiked with the onset of the European sovereign debt crisis.

Our results are robust to alternative weights in the application of Hirano et al. [2003b] that are based on other fiscal variables or timings. Not using any weights and thus treating the undercapitalization status as exogenous, however, reveals that our loan-level results could not have been uncovered. It therefore seems to be the case that the perverse lending incentives are particularly strong for banks whose undercapitalization is a consequence of forbearance. Hence, the fact that governments ″kicked the can down the road″ on banking sector repair affected subsequent outcomes in two ways. First, they delayed fiscal costs, which had to be borne in the subsequent sovereign debt crisis in the form of larger amounts of quasi-fiscal central bank support and a weakened credit supply to the real economy. Second, they provided perverse lending incentives to banks on which they exerted forbearance, leading to misallocation of capital in the form of ″zombie″ lending and search-for-yield behavior.

[6] Similar behavior has been documented in Jiménez et al. [2017].

The remainder of the paper is organized as follows. Section 3.2 discusses the related literature. Section 3.3 introduces the dataset, focusing especially on the novel, hand-collected dataset comprising all government interventions benefiting eurozone banks over the 2007 to 2012 period. Section 3.4 presents empirical evidence on forbearance by fiscally weaker governments in the European banking sector during the financial crisis from 2007 to 2009. In Section 3.5, we derive which banks are undercapitalized and describe the methodology of our treatment effects model. Sections 3.6 and 3.7 describe the main results for bank-level outcomes and lending decisions over the 2009 to 2012 period. The analyses of government debt holdings and the portfolio shifting of undercapitalized banks are in Section 3.8. Section 4.7 concludes.

3.2 Related literature

Our paper contributes to several strands of literature. First, it relates to the literature on regulatory forbearance that dates back to at least the 1980s and the discussion of "zombie thrifts" in the U.S. by Edward Kane and other authors, showing that regulatory forbearance is not a new phenomenon but one that has played out over decades (see, e.g. Kane [1989] and references therein). More recent research in this area focuses on the drivers of (regulatory) forbearance, e.g. why governments do not intervene in the banking sector, even though it would be optimal from a general welfare perspective. Governments postpone the resolution of distressed banks if there are many weak banks in the banking sector (Acharya and Yorulmazer [2007]: Acharya and Yorulmazer [2008]; Kroszner and Strahan [1996]; Hoshi and Kashyap [2010]; Brown and Dinç [2011]) or for political economy reasons, such as timing in electoral cycles (Brown and Dinc [2005]; Imai [2009]; Bian et al. [2017]). Our paper highlights empirically - as posited by some of this literature - that fiscal capacity is an additional driver behind (regulatory) forbearance. In addition to most of the previous literature, we also investigate the implications of (regulatory) forbearance. Gropp et al. [2017], for example, show that regulatory forbearance in the U.S. - due to the Federal Deposit Insurance Corporation's (FDIC) decision not to let banks fail - affects growth and employment in some regions; we show that a sovereign's debt overhang can significantly impede an undercapitalized banking sector's recovery after a financial crisis, especially its financial stability, credit supply and risk-taking incentives.

Second, our paper adds to the growing literature investigating the cost-benefit trade-offs involved in government interventions in the banking sector. The main benefit is that recapitalizations help alleviate negative externalities from failing the severely undercapitalized banks (Diamond et al. [2001]). Costs mainly comprise large fiscal outlays (Acharya et al. [2014]) and moral hazard arising from bailout expectations (Mailath and Mester [1994]; Dam and Koetter [2012]; Fischer et al. [2014]).[7] Several papers analyze this trade-off during the GFC, focusing predominantly on the Capital Purchase Program in the United States (Veronesi and Zingales [2010]; Bayazitova and Shivdasani [2012]; Li [2013]; Duchin and Sosyura [2014]; Berger et al. [2019]; Black and Hazelwood [2013]). Evidence from the U.S. suggests that recapitalizations stabilized bank lending growth, but also increased lending to riskier borrowers. In contrast, we investigate government interventions during the European financial and sovereign debt crisis.[8] Homar and van Wijnbergen [2017] show that timely bank recapitalizations reduce the duration of recessions using an international sample of banking crises. We provide new evidence that government interventions need to be large enough to overcome banks' debt overhang problems, a theme reminiscent of the work of Caballero et al. [2008], Diamond et al. [2001], Giannetti and Simonov [2013], and Brei et al. [2013].

Finally, our paper relates to the literature on the role of bank capital, particularly during financial crises. Berger and Bouwman [2013] document the importance of capital for banks, particularly medium- and large-sized banks, during crises. Several studies document that higher capital was associated with lower probability of bank failure during the 1990 credit crunch (Cole and Gunther [1995]; Estrella et al. [2000]; Wheelock and Wilson [2000]) and during the 2008–2009 financial crisis (e.g. Cole and White [2012]; Berger et al. [2016]). Beltratti and Stulz [2012] find that bank capital is key to understanding bank performance during the subprime crisis, and Fahlenbrach et al. [2012] show that poorly capitalized banks during the Russian debt crisis also performed poorly during the subprime mortgage crisis. By evaluating aggregated time series of sovereign and financial shocks simultaneously, Manzo and Picca [2020] show that fiscal capacity of governments is an important determinant of sovereign shocks, which in turn spill over to the financial sector. We show on a disaggregate level that banks that were left un-

[7] While most theoretical and empirical papers highlight the negative incentives arising from government interventions associated with decreased investor monitoring, some authors highlight that bailouts may also lower moral hazard as government guarantees increase the charter value of banks (Keeley [1990]; Cordella and Yeyati [2003]).

[8] Homar [2016] investigates the benefits of bank recapitalizations for publicly traded banks, highlighting that recapitalizations need to be large enough, but does not investigate the costs of interventions.

dercapitalized by their governments during the GFC were more likely to eventually require greater government support, performed worse, lent poorly, and searched for yield in portfolio composition decisions.

3.3 Data

3.3.1 Government interventions

This paper builds on a novel, hand-collected dataset comprising all government interventions for eurozone banks over the 2007 to 2012 period. Our primary data source is the State Aid Register of the European Commission (EC), which contains detailed information on government interventions in the European banking sector. The Treaty on the Functioning of the European Union (TFEU) generally prohibits government support to individual companies but government support can be admissible in exceptional cases, such as to "remedy a serious disturbance in the economy of a Member State" (TFEU Article 107(3.b)). Any such exception must be reviewed and approved by the EC on a case-by-case basis and is documented in the State Aid Register.

While the State Aid Register collects government interventions in the entire EU, we restrict our sample to eurozone banks to ensure that all banks in our sample have equal access to the ECB facilities (including non-standard monetary policy measures such as the LTRO).[9] Since the LTROs were provided with full allotment in our sample period, there was no heterogeneity in the access to the ECB funding across banks. Thus, we do not expect our results to be biased by the existence of LTRO.

We start building our database by manually extracting information from all State Aid cases listed in European Commission for the 2007 to 2012 period.[10] Government support can be approved for one of two cases: (i) as an ad hoc support measure to an individual bank, or (ii) as a sector-wide scheme making available a maximal amount for a certain aid measure and being accessible to eligible banks.[11]

For reasons of confidentiality, not all details of government support measures are made available in the State Aid Register. Also, decisions on sector-wide schemes do not

[9] We exclude Cypriot banks from our sample given the extraordinary dependence of the Cypriot banking sector on foreign funding sources.

[10] Link to State Aid Register.

[11] Table A1 in the Online Appendix provides an example excerpt from this list for the case of Austria. Table A2 in the Appendix provides an excerpt from a State aid case for the recapitalization of the Austrian bank Hypo Tirol.

contain information on individual beneficiaries. Therefore, when necessary, we augment the data with information from banks' press releases, information from banks' regular reporting activities, regulators' and central banks' reports, and newspaper articles. For every State Aid case number, we further cross-check whether approved intervention measures have been implemented.

As in Laeven and Valencia [2008], we classify government support into four categories: (1) recapitalizations, (2) guarantees, (3) other liquidity support and (4) troubled asset relief.[12] Recapitalizations comprise all measures involving government-funded capital increases and conversions of existing capital or hybrid instruments into higher-order capital instruments.[13] Guarantees comprise all government guarantees on non-deposit liabilities, including both existing and newly issued liabilities. Other liquidity support comprises all interventions other than guarantees that are targeted at stabilizing a bank's liquidity.[14] Finally, troubled asset relief programs are government interventions targeted at removing impaired or defaulted assets from a bank's balance sheets by means of asset sales or guarantees.[15]

3.3.2 Bank-level and macro-level data

Sample construction

We obtain bank-level financial data for the 2007 to 2012 period from the Bureau van Dijk Bankscope database. Consistent with the literature (e.g. Sufi [2007]), all information is aggregated to the ultimate parent level using shareholder information from Bankscope and various other sources. We remove all banks that receive a government intervention but cannot be matched to the Bankscope database. We also drop banks whose ultimate parent is not incorporated in a eurozone country, as the propensity of a bailout for these

[12] We exclude all policies that were not put into use during the financial crisis, such as deposit freezes. We also exclude sector-wide policies such as changes in sector-wide deposit guarantees, which simultaneously benefited all banks in a country.

[13] Banks can be recapitalized using cash, ordinary shares, other Core Tier 1 capital instruments, preferred shares, silent participations, hybrid capital instruments, commitment letters and rights issues.

[14] Our definition of liquidity support differs from the one employed in Laeven and Valencia [2008], where liquidity support indicates liquidity support from the central bank.

[15] For each type of intervention, our database collects a wide range of characteristics including the identity of the beneficiary, the intervention amount, the specific design of the measure, its remuneration and possible conditions for the beneficiary. We also collect the announcement date (when available), the implementation date, the approval date by the EC and whether the intervention was granted as part of a sector-wide intervention scheme. We provide a detailed overview of all information as to government interventions recorded in our dataset in an Online Appendix.

banks likely depends on the parent's home country. The dataset is further constrained to large banks and those of domestic importance—those whose failure creates a threat of financial contagion or has a large negative impact on the domestic economy. That is, we keep banks with a market share larger than 1% (measured in bank size/size of the national banking sector), with size of at least 10% of GDP, balance sheets larger than €1 billion, or banks that are among the 5 largest banks in the country.

We further exclude banks with very high Tier 1 ratios ($> 30\%$) or equity-to-assets ratios ($> 20\%$). All those cleaning steps leave us with a sample of 830 banks, of which 76 received at least one form of government intervention. Finally, we augment our data with country-level variables from Eurostat, the World Bank and the IMF.

Summary statistics

Cross-sectional summary statistics for bank-level variables are shown in Panel A of Table 3.B.1 for the baseline year 2007. Banks show considerable variation in their overall condition prior to the financial crisis. For example, the equity-to-assets ratio ($Equity/TA$) has a cross-sectional mean of 6.51% with a standard deviation of 2.75%. There is also considerable variation in other variables, such as loan loss provisions ($LLP/Loans$) and NPLs ($NPLs/Loans$). Cross-sectional summary statistics for macro-level variables in 2007 are shown in Panel B of Table 3.B.1. The variation in current account balances is striking: it ranges from a current account deficit of -14.0% to a current account surplus of 9.9%. Similarly, the maturing government debt as a share of GDP ranges from 1.2% to 18.1%.

[Table 3.B.1 about here]

3.3.3 Loan-level and firm-level data

We obtain loan-level data from the Thomson Reuters LPC DealScan database, which provides detailed information on European syndicated loans including information on lenders as well as loan contract terms. For banks to be included in the sample, we follow the previous literature (e.g. Ivashina [2009]; Heider et al. [2019]) and require that banks must serve as lead arranger in the syndicate.[16] If the loan allocation between

[16]Following Ivashina [2009], a bank is classified as lead arranger if it has any one of the following lender roles in DealScan: administrative agent, bookrunner, lead arranger, lead bank, lead manager, agent or arranger. The subsequent results are robust to extending the sample of lead arrangers to match the defi-

syndicate members is unknown, we divide the loan facility equally among syndicate members. Also following the previous literature (e.g. Acharya et al. [2018]; Gropp et al. [2019a]), we transform the data and calculate the annual outstanding exposure of bank b in country c to non-financial firm j, using the maturity information on each loan at the end of each year.

We hand-match DealScan lenders to Bankscope at the ultimate parent level and match DealScan borrowers in our sample to firms in the Amadeus database. The final loan-level sample comprises 209 banks that arrange loans to 8,321 non-financial firms.[17]

3.4 Do weak governments delay interventions?

Governments may postpone recapitalizations by issuing rolling guarantees, by injecting just enough capital to avoid immediate insolvency, or by allowing banks to hide their losses. This section investigates the determinants of a government's decision not to resolve a bank's debt overhang immediately, but to practice (regulatory) forbearance. We use Cox regression models to formally investigate the role of a country's fiscal capacity and the overall capitalization of the banking sector for the timing and type of an intervention.

3.4.1 Methodology

Theory suggests that forbearance and postponing costly capital interventions is an attractive alternative for fiscally constrained governments as new debt can only be issued at the expense of the sovereign's creditworthiness (Acharya et al. [2014]). Based on this theory, we ask two questions. First, are fiscally constrained governments as likely as unconstrained countries to provide recapitalizations? Second, are they equally likely to support distressed banks, when we do not take into account the type of support (recapitalization, liquidity support)?

nition in Heider et al. [2019]. In this case, lead banks comprise all banks that provide 100% of a given loan or act as lead bank, lead manager, (mandated) lead arranger, joint arranger, co-lead arranger, co-arranger, coordinating arranger, mandated arranger, (administrative) agent, or bookrunner.

[17] Possible differences in the number of lead arrangers in this paper in comparison to other papers on syndicated lending in the European banking sector (e.g. Heider et al. [2019]) may be due to the match of lenders to the Bankscope database rather than to the smaller SNL Financials database.

We study determinants of government interventions in the 2007 to 2009 period, using an exponential hazard model similar to Brown and Dinc [2005].[18] The hazard rate $h_{AID,i}(t)$, $AID \in \{Recap, Any\}$, is the instantaneous probability that bank i receives government support AID at time t, conditional on not having obtained AID prior to t. h_{Recap} is the hazard rate for being recapitalized, and h_{Any} denotes the hazard rate for obtaining any type of intervention. We follow banks from the date Lehman filed for insolvency (15 September 2008) until one of the two following exit events: (i) the bank receives its first intervention $AID \in \{Any, Recap\}$ or (ii) the end of the sample period, 31 December 2009, is reached. In the Cox regression framework, the hazard rate takes the exponential form

$$h_{AID,i}(t) = h_{AID,0}(t) * exp(\beta_0 X_{i,t-1} + \beta_1 b_{c,t-1} + \beta_2 m_{c,t-1}), \tag{3.1}$$

where $h_{AID,0}(t)$ is the baseline hazard; $X_{i,t-1}$ is a vector of bank-specific characteristics; $b_{c,t-1}$ are banking-sector-specific characteristics; and $m_{c,t-1}$ are macroeconomic variables. The analysis is conducted based on daily intervention data but is robust to monthly aggregation. Standard errors are clustered at the country level, allowing government interventions to be correlated within a country.

Fiscal capacity. The main determinants for our model are measures of fiscal capacity. Different proxies have been proposed in the literature. One key measure is a country's tax revenues ($GovernmentRevenue$) expressed as a percentage of GDP (Dincecco and Prado [2012]). A larger income increases the capacity to recapitalize banks in distress (Stavrakeva [2020]). Another widely used factor is the total debt stock ($Debt/GDP$) also measured in units of GDP (e.g. Demirgüç-Kunt and Huizinga [2013]). However, high total debt is only a potential problem if government revenues are low and/or if debt has to be refinanced. We thus also include a measure for maturing debt, by dividing the stock of outstanding government debt by its average maturity ($MaturingDebt(\%GDP)$). This allows us to distinguish between countries that have a high outstanding debt stock but a low current debt service and countries with a low stock but a high current debt service, since only the latter should be relevant for forbearance. Lastly, we use the current account surplus/deficit ($CABalance$) as a potential determinant as fiscal constraints

[18] Shambaugh et al. [2012] highlight the advantage of hazard models in forecasting bankruptcy. We use logit regressions as robustness checks. The results are very similar and remain unreported for brevity.

might become binding when a country borrows from abroad (Freund and Warnock [2007]).[19]

Figure 3.A.1 about here

Figure 1 shows that these metrics of fiscal constraints show substantial cross-sectional variation, especially between GIIPS and other Eurozone countries. In case of debt-to-GDP, government revenues-to-GDP, and current account balance, the differences were large at the time of the onset of the global financial crisis; interestingly, debt-to-GDP (and also maturing debt-to-GDP) worsen for GIIPS relative to other Eurozone countries after the global financial crisis, whereas the current account balance improves from being in deficit towards neutrality as for the other Eurozone countries.
A further measure that we considered is a country's current budget balance. It is a short-term flow measure, meaning it will quickly react to dynamics that might be relevant for bailout provision such as a deterioration of the macroeconomic environment which the government counteracts with a fiscal stimulus package. Moreover, it might be subject to reverse causality, if some bank aid measures were provided in 2007 as this would immediately and significantly affect the budget balance, while it would only have minor effects on government revenues or the stock of outstanding government debt. Hence, we decided not to include the budget balance in our study.

Banking sector. As a banking-sector-specific variable, we include the average book equity-to-assets ratio ($Avg.EquityRatio$). Brown and Dinç [2011] show that governments are less likely to intervene if the banking sector as a whole is undercapitalized (too-many-to-fail effect). As a further relevant determinant of the need for bailouts, we include the level of household debt over GDP ($HHDebt/GDP$). Mian et al. [2017] show that a high level of household debt is a strong predictor of economic downturns because of the sensitivity of mortgage credit to house price busts, which is exactly what was observed during the GFC. We also include the number of banks that have already received a bailout ($NumberBailouts$).

Bank characteristics. We include bank-level characteristics to control for bank health and their differential probability of becoming distressed. Specifically, we include bank

[19] If a country is not borrowing from abroad (and c.p. has a current account surplus), it is not at risk of becoming constrained as it can engage in financial depression to secure its funding, e.g. through an increase in domestic taxes. However, if a country is borrowing from abroad on a net basis, it is subject to market discipline and possible sudden stops when foreign investors become unwilling to roll over their funds. Sudden stops have detrimental effects on future tax income through output contractions, increases in unemployment and asset price declines (Freund and Warnock [2007]).

size ($TotalAssets/GDP$), equity-to-assets ratio ($Equity/TA$), wholesale funding dependence ($STfunding/TA$) and profitability ($ROAA$). We hypothesize that larger banks with lower capital ratios are more likely to obtain support. Short-term funding dependence, in addition, renders banks vulnerable to interbank funding freezes. ROAA might be an indicator for a sound business model as well as high pre-crisis risk-taking. All variables are measured at the end of the year preceding day t in the hazard model.

Elections. As in Brown and Dinç [2011], we include proxies that relate to the political environment in each country. We include the logarithm of the time until the next election ($LogTimetoElection$) and an index indicating to what extent the current parliament is supporting the European Union ($ProEU$).

3.4.2 Determinants of government bailouts

Table 3.B.2 reports the main results. We only show the measures of fiscal capacity; the full specifications are reported in an Online Appendix to this paper. The dependent variable is h_{Recap} in Panel A of Table 3.B.2. While the control variables are included in all regressions, we sequentially include proxies for fiscal capacity.[20]

Table 3.B.2 about here

As the main determinant of a country's fiscal strength, we include government revenues in all four regressions. Throughout all specifications, this variable is an economically and statistically significant predictor of recapitalizations. In columns 1 to 3, we add different additional proxies for the financial well-being of a country. First, we add the total debt-to-GDP ratio. While the coefficient shows the right sign - higher debt makes bailouts less likely - the result is not statistically significant. However, for any given debt level, a higher share of debt that has to be repaid in the current year induces immediate budgetary constraints and thus should reduce the incentives to recapitalize banks. We find that a large proportion of maturing debt (in the same year as the bailout decision) decreases the hazard rate and thus the likelihood of a recapitalization (column 2). When

[20]The control variables are as expected. Larger banks and those that have more short-term funding are more likely to be recapitalized. Banks with higher pre-crisis equity capital ratios and more profitable banks are less likely to be recapitalized. Moreover, coefficient on Avg. Equity Ratio echoes the results from Brown and Dinç [2011] that governments are more likely to delay an intervention when the banking sector as a whole is weakly capitalized. A new government is less likely to recapitalize a bank, while more Pro-EU governments are more likely to provide direct recapitalizations to banks.

looking at the current account balance in column 3, the coefficient again shows an intuitive sign (higher current account surplus predicts higher likelihood of bailouts), but is not significant. In column 4, we run a horse race of all those three explanatory variables on top of the government revenues. We observe that maturing debt stays highly significant and important in size. Moreover, both the current account balance and the total debt level turn significant in this specification. A higher current account is associated with a higher likelihood of recapitalizations. A higher debt level is, too, suggesting that after partialling out the effect of the debt service burden, a higher debt level corresponds to a country's willingness to spend, thus making a recapitalization more likely. Overall, the results consistently show that countries that had more fiscal capacity when entering the GFC in 2008 to 2009 were more likely to recapitalize their banks.[21]

In Panel B of Table 3.B.2, we show the results, where the dependent variable is Any, i.e. we predict the likelihood of any kind of government intervention (recapitalization or liquidity support). None of our measures of fiscal strength turns out to be a significant predictor of government interventions.

3.5 Identifying undercapitalized banks at the end of 2009

3.5.1 Methodology

In the following we want to study the implications of banks leaving the GFC period in a status of undercapitalization. Naturally, this status is by no means exogenous. It depends on the capitalization of the bank before the crisis shock hits, its lending portfolio, profitability, and many other bank-specific factors. Moreover, as shown above, it strongly depends on whether the bank was located in a country whose government was able to provide a recapitalization if needed. That is, the probability of being undercapitalized at the end of 2009 depends on a bank's performance in pre-crisis years as well as the fiscal capacity of the local government. In order to obtain a plausibly exoge-

[21] For robustness, we also add additional CAMELS proxies, including non-performing loan ratios, age, and loans-to-deposit ratios. The coefficient estimates on both bank-level characteristics and macro-level variables are unchanged, while the R^2 remains largely unchanged. We also substitute ROAA with the z-score—the results remain quantitatively and qualitatively unchanged. The analysis is also robust to setting the starting point of the financial crisis to 9 August 2007, when the withdrawal of BNP Paribas from three hedge funds marked the beginning of a liquidity crisis. Logit regressions produce virtually identical results to Cox regressions. These results remain unreported for brevity.

nous measure of undercapitalization, we therefore have to purge these factors from our measure.

To formalize this idea, we rely on an inverse probability weighting method developed by Hirano et al. [2003b] and recently used in a time series context by Jordà and Taylor [2016], among others. The basic idea of this method is to remove all observable factors that are associated with the treatment assignment. For this purpose, the treatment probability is estimated and used to reweight the sample in all subsequent treatment effect models to reduce, or in the optimal case even eliminate, the bias from endogenous treatment assignment.

In our case, the bank-level treatment is "being undercapitalized at the end of 2009", i.e. after the GFC. In order to run a logit model for estimating the treatment probability, we need to construct a binary indicator for undercapitalization. Hence, we define a bank as being undercapitalized if one of the following three conditions holds at the end of 2009: i) its Tier 1-capital ratio is below 8%[22], and if Tier 1 ratio data is not available, ii) its equity-to-assets ratio is below 3% (the BCBS leverage ratio requirement), or iii) its NPL-to-loans ratio is in the top 5% of all banks in our sample. Our results are not very sensitive to the choice of these criteria. Removing the third criterion, or varying the thresholds for the first two criteria, does not qualitatively alter our results.

We then estimate a logit model predicting the treatment status based on bank-level and macro-level determinants (including our measures of fiscal capacity) and interactions of bank-level and fiscal variables as of end-2007. The results are robust to using inputs as of end-2006 (see Table 3.B.10). However, we use bank and government characteristics as of 2007 as they are arguably better predictors of post-crisis outcomes.

$$\begin{aligned} Undercap_i =& \frac{exp(\beta X_i)}{1 + (exp(\beta X_i)}, \\ \text{where} \quad \beta X_i =& \beta_0 \times X_{i,2007} + \beta_1 \times b_{c,2007} + \beta_2 \times m_{c,2007} + \beta_3 \times X_{i,2007} * m_{c,2007}. \end{aligned} \tag{3.2}$$

It is important to interact bank-level and fiscal measures to create within-country variation in the predictions at the bank level. Moreover, the interactions are economically sensible and important. A government with higher fiscal capacity can afford to bail out bigger banks, banks that are better capitalized, and banks that are less profitable. From

[22] The FDIC defines the threshold for undercapitalization as a Tier 1-capital ratio below 4% for U.S. banks. In Europe, however, banks benefit from more lenient policies on government debt, for example, the absence of which would result in lower Tier 1-capital ratios (cf. Kirschenmann et al. [2017]). As a result, 8% is roughly the first quintile in our sample, substantially below the mean of 10.7%.

this regression, we obtain the fitted values ($\widehat{Prob_i}$) and use them to calculate "inverse probability weights" (IPW):

$$IPW_i = \frac{1}{\widehat{Prob_i}} \quad \text{for treated,} \tag{3.3}$$

$$IPW_i = \frac{1}{1-\widehat{Prob_i}} \quad \text{for non-treated.} \tag{3.4}$$

The distinction in the weight calculation between treated and non-treated is important. To reduce the endogeneity bias, a higher weight needs to imply a less predictable treatment status. Hence, if our model failed to predict that a bank is going to be treated, we want a higher weight than if the treatment was predicted. Thus, the weight formula for treated banks is a decreasing function of the treatment likelihood obtained from estimating Equation 3.3, and vice versa for non-treated banks.[23]

3.5.2 Descriptive statistics

We report descriptive statistics in Table 3.B.3. In Panel A of Table 3.B.3, we show which banks received government support during the 2008 to 2009 GFC and which are classified as undercapitalized. Around 10% of the banks in our sample (81 out of 830) are classified as undercapitalized according to our measure. Out of those 81 banks, 8 actually received a recapitalization, which therefore seemed to have been insufficient to stabilize those banks. The other 27 recapitalizations we observe were successful in that the receiving banks are not classified as undercapitalized in 2009. These numbers suggest that recapitalizations were, on average, a very prolific tool to stabilize banks.

[Table 3.B.3 about here]

Panel B of Table 4 shows the share of undercapitalized banks by country at the end of 2009. The countries with the largest share of undercapitalized banks are Ireland (IE), Slovenia (SI) and Italy (IT), while France (FR) and Germany (DE) exhibit the lowest share of undercapitalized banks, which is reasonable as these countries implemented

[23] This method has been applied in various economic contexts over recent years, e.g. Angrist et al. [2018], Yim [2013], Jordà and Taylor [2016], Acemoglu et al. [2019], Kuvshinov and Zimmermann [2019]. From a technical point of view, advantages over a simple OLS model with control variables are: higher efficiency (Hirano et al. [2003b]), possibility of capturing non-linear relationships between covariates and the treatment assignment (Rosenbaum and Rubin [1983]), doubly robust estimation structure (Jordà and Taylor [2016]) and measuring of interpretable probability weights.

large-scale recapitalization measures and both belong to the group of fiscally strong countries.

3.5.3 Likelihood of being undercapitalized

Table 3.B.4 reports the results of the logit model described in Equation 3.3 to calculate the IPW. Table 3.B.4 shows that larger and better-capitalized banks are less likely to be undercapitalized post-GFC in countries with higher (tax) revenues, i.e. in which governments have more fiscal space.

[Table 3.B.4 about here]

Similarly, columns 1 to 3 show that our other measures for fiscal capacity - total debt, maturing debt, and the current account balance - all interact with bank variables in determining the likelihood of a bank being undercapitalized. Column 4, similar to section 3.4, runs a horse race of all fiscal variables, highlighting that all of them have their distinct importance. However, the average variance inflation factor for those fiscal variables in column 4 is around 25, which is beyond any acceptable threshold. Due to possible multicollinearity of the covariates used in the specification reported in column 4, we use column 2 as our baseline regression model.[24]

We want to stress the finding that the interplay of fiscal capacity and bank characteristics is a very important determinant of banks' capitalization outcome. Hence, specifying the inverse probability weighting model the way we did is crucial to fully capture the endogeneity in the undercapitalization status driven by differences in fiscal capacity across countries.[25]

Overall, the results reported in Table 3.B.4 show that being undercapitalized in 2009 is not an exogenous event, but depends on a variety of factors. To purge these factors, we use the IPW obtained from the baseline logit in Table 3.B.4, column 2, when evaluating the effect of being undercapitalized on real economic outcomes in the following sections.

[Figure 3.A.2 about here]

[24] We provide robustness tests using weights obtained from the other regression models in the Online Appendix.

[25] Note that a country fixed effect would not suffice to adequately model the underlying mechanisms since the fiscal capacity interacts heavily with bank-level characteristics.

Panel (a) of Figure 3.A.2 shows the difference of the average IPW per country and 1.[26] The higher these values, the less the outcomes can be linked to the observable factors used as explanatory variables in Table 3.B.4. This difference therefore helps us to assess the extent of discretion applied by national governments in their recapitalization decision. We find the five GIIPS (Greece, Ireland, Italy, Portugal, and Spain) countries in the top 6 of the ranking in Panel (a) of Figure 3.A.2. Similarly, Panel (b) of Figure 3.A.3 shows a scatterplot of the same country-level average of IPW and the government revenue-to-GDP ratio. The plot clearly suggests a negative relationship, i.e. fiscally stronger governments exerted less discretion.

3.5.4 Understanding inverse probability weights

[Figure 3.A.3 about here]

Figure 3.A.3 uses an example to demonstrate how inverse probability weighting can be understood in our setup. We document above that countries provided bailouts to their banks as a function of their capitalization. This is shown by the vertical black lines in the graph, where Ireland, Spain and Germany are ranked by their respective government revenues from low to high. The vertical black lines imply that Spain and Germany bailed out banks that had higher capital ratios compared to Ireland. That is, comparing an Irish bank (with a 4.25% capital ratio in 2007) to a German bank (also with a 4.25% capital ratio in 2007) at the end of 2009 ignores that Irish banks have never been bailed out with such a high capital ratio; however, a bailout was quite likely for a German bank, arguably because of Germany's fiscal strength. Therefore, the inverse probability weighting allows us to remove the differences indicated by the vertical black lines, which would induce a bias in subsequent treatment effect estimations.

By removing all the bank-specific and country-specific drivers of undercapitalization, as well as their interactions, the resulting weights then give us an estimate of the extent of discretion applied by the governments when deciding about recapitalizations. An undercapitalized bank with a high weight is a bank that should have been bailed out (given its situation) and could have been bailed out (given its governments' situation), but was not, and vice versa for better-capitalized banks. As highlighted in the section above, these cases of elevated discretion are themselves negatively correlated with fis-

[26] An IPW of 1 for the treated (i.e. undercapitalized) bank suggests that the treatment is endogenous, i.e. being undercapitalized is perfectly predictable based on observable characteristics.

cal stability. Moving forward, we thus interpret our bank results as the impact of banks being undercapitalized due to governmental discretion linked to fiscal weakness.

3.6 Undercapitalization and bank balance sheets

Delaying government interventions might cause distressed banks' health to further deteriorate, as necessary recapitalizations are either omitted or severely limited. Undercapitalized banks likely have insufficient capital buffers to withstand future shocks. Moreover, a debt overhang might increase agency costs due to moral hazard, including risk-shifting (Meckling and Jensen [1976]; Diamond et al. [2001]) and zombie-lending (Peek and Rosengren [2005]; Giannetti and Simonov [2013]; Blattner et al. [2019]).

3.6.1 Methodology

In a first step, we ask whether banks that were left undercapitalized after the 2008–2009 GFC further deteriorate in their health relative to other banks. We estimate the following cross-sectional weighted-least squares (WLS) regressions, where we use the IPW as weights:

$$\Delta Y_{i,09-12} = \alpha + \beta \times Undercap_i + \gamma X_{i,09} + u_i, \tag{3.5}$$

$$Y_i = \alpha + \beta \times Undercap_i + \gamma \times X_{i,2009} + v_i. \tag{3.6}$$

The dependent variable $\Delta Y_{i,09-12}$ is the log change in characteristic Y of bank i over the 2009 to 2012 period. Y_i are outcome variables measured at the end of 2012. The set of Y_i comprises: equity-to-assets ratio, Tier 1-capital ratio, gross loans, loan loss provisions, share of NPLs, return on average asset, net interest margin, and the risk weighted assets-to-total assets ratio. Bank-level variables $X_{i,09}$ comprise total assets to domestic GDP ($TotalAssets/GDP$), the equity-to-assets ratio ($Equity/TA$), the loans-to-deposits ratio ($Loans/Deposits$) and return on average assets ($ROAA$), as of end-2009. These measures are supposed to capture the state of each bank at the beginning of the evaluated period with respect to its size, health, funding structure, and profitability.

3.6.2 Undercapitalization and bank balance sheets

The results of the balance sheet impact regressions are summarized in Panel A of Table 3.B.5. Columns 1 and 2 highlight that while undercapitalized banks' equity-to-asset ratios further declined in the years 2009 to 2012, their risk-weighted Tier 1-capital ratio increased. This suggests that these banks did not build up additional equity but instead pushed the risk weights downward by lending less to risky borrowers.

[Table 3.B.5 about here]

Column 4 shows that the level of loan loss provisions of undercapitalized banks went up distinctly from 2009 to 2012, indicating a badly performing lending portfolio inherited from the GFC period. All these results are highly significant and robust to using alternative IPWs.

Interestingly, NPLs did not increase over the 2009 to 2012 period despite the increase in loan loss provisions (column 5). A possible interpretation is that undercapitalized banks continued to extend loans to these borrowers to avoid writing down their exposures. The return on assets is somewhat lower for undercapitalized banks (column 6). Net interest margins and risk intensity (columns 7 and 8) are unaffected by undercapitalization.

How do undercapitalized banks perform during the sovereign debt crisis? In particular, we investigate three dimensions: whether a company needs a recapitalization, files for insolvency or needs funding from the LTRO introduced in December 2011 and continued in March 2012. We report the results in Panel B of Table 3.B.5.

While we find an economically meaningful (but statistically insignificant) positive effect of undercapitalization on the likelihood to be recapitalized, and a lower likelihood to survive, we find a highly economically and statistically significant effect on LTRO in that undercapitalized banks borrow substantially from the LTRO facilities compared to better-capitalized peers. This shows that leaving banks in a state of undercapitalization, by not providing sufficient recapitalizations during the GFC, induced higher funding needs for these banks down the line, again to be borne by governments' budgets, showing that governments just kicked the can down the road.

The results are not sensitive to the chosen weighting scheme, as Panels A and B in Table 3.B.11 show. An alternative weighting scheme and no weighting scheme at all provide similar albeit economically weaker results with lower explanatory power (R^2).

3.7 Undercapitalization and bank lending decisions

Figure 3.A.4 shows the "excess reduction" in lending by undercapitalized banks, i.e. the reduction in lending relative to all other banks, for all firms (left bars), for "high-risk" firms (middle bars) and for "zombie" firms, in particular (right bars). The grey bars show the descriptive differences in the lending behavior, while the black bars show the estimated coefficients from regressions described later in the text. We leave the formal definition of "high-risk" and "zombie" firms to the main text below. The differences are striking. While undercapitalized banks significantly reduce their lending more relative to other banks, especially to riskier borrowers, they increase lending to "zombie" firms. In other words, the remaining equity capital of already constrained banks appears to be withdrawn from risky, "non-zombie", firms and tied up in lending to "zombie" firms.

[Figure 3.A.4 about here]

3.7.1 Loan volume

So far we have seen evidence for undercapitalized banks cutting back lending (Figure 3.A.4, left bars; Table 3.B.5, column 3). In this section, we want to drill down further into the lending decisions by undercapitalized banks by investigating the lending behavior at a more granular level.

We start our loan-level analysis by studying the effect of government interventions on overall loan supply. Our main dependent variable is $\Delta Loan_{09-12,i,c,j}$, which captures the change in outstanding loan exposure of bank i in country c to firm j from the year just after the financial crisis, 2009, to the year 2012. Similar to Peydró et al. [2017], we define the change in outstanding loan exposure following the definition of Davis and Haltiwanger [1992] as[27]

$$\Delta Loan_{09-12,i,c,j} = \frac{Loan_{12,i,c,j} - Loan_{09,i,c,j}}{0.5 * Loan_{12,i,c,j} + 0.5 * Loan_{09,i,c,j}}. \tag{3.7}$$

[27]Using this definition has two main advantages. First, we avoid the regression results being driven by outliers as $\Delta Loan_{09-12,i,c,j}$ lies on the closed interval [-2,2]. Second, the measure facilitates the treatment of zeros, where either no bank–firm relationship exists in 2009 but emerges over the 2010 to 2012 period, or the bank–firm relationship is terminated between 2009 and 2012.

We estimate the following WLS model,

$$\Delta Loan_{09-12,i,c,j} = \beta \times Undercap_i + \gamma X_{i,09} + \eta_j + \eta_c + u_{i,c,j}, \tag{3.8}$$

where all variables are defined as before and bank-level characteristics are measured at the end of 2009. All variables are weighted using the IPWs obtained in section 3.5. Following Khwaja and Mian [2008], we exploit the fact that some firms borrow from more than one bank and use a within-firm estimator to disentangle loan supply from loan demand. Specifically, firm fixed effects η_j control for observable and unobservable firm characteristics that may affect firm-level demand. Firm fixed effects are identified by multiple bank–firm relationships, where firms borrow from at least two distinct borrowers. Bank-level control variables $X_{i,09}$ comprise log total assets ($LogTotalAssets$), the equity-to-assets ratio ($Equity/TotAssets$), the return on average assets ($ROAA$), and the NPLs-to-loans ratio ($NPL/Loans$), as of end-2009.[28] We also include country-level fixed effects to control for country-level differences in credit supply. Standard errors are clustered at the bank level.[29]

We present the results for the baseline specification in column 1 of Panel A of Table 3.B.6. We find that undercapitalized banks significantly reduce their loan supply, which is consistent with the balance sheet regressions shown above. Undercapitalized banks reduce their loan supply by 14 p.p. more than better-capitalized banks.

[Table 3.B.6 about here]

As a robustness check, we also employ other dependent variables to measure changes in loan supply (columns (2) and (3)). First, we use the first difference in log loan exposure of bank i in country c to firm j, $\Delta logLoan = log(1+Loan_{12,i,c,j}) - log(1+Loan_{09,i,c,j})$, as in Peydró et al. [2017].[30] Second, we follow Peek and Rosengren [2005] and Giannetti and Simonov [2013] and use the indicator $LoanIncr_{i,c,j}$ that takes value 1 if bank i increases its loan exposure to firm j from 2009 to 2012, and 0 otherwise. The results confirm the robustness of the result in column (1): undercapitalized banks generally reduce their loan supply from 2009 to 2012.

[28] This set of controls is the same set as chosen in Acharya et al. [2018].

[29] We follow Abadie et al. [2017]. We interpret our reweighted sample as a quasi-experimental setting implying the need to cluster at the treatment provision level. Since bailouts are provided at the bank level, we cluster at the bank level.

[30] For cases where $Loan_{12,i,c,j} = 0$, we normalize the growth rate to -1.

Simple bank lending theory suggests that weakly capitalized banks lend less to risky borrowers, since the regulatory risk weights make such loans capital-intense. We investigate this theory by including a measure of borrower risk ($LowRating$) in the interaction terms to investigate lending decisions with respect to borrower quality and estimate the following WLS model:

$$\Delta Loan_{09-12,i,c,j} = \beta_1 \times Undercap_i + \beta_2 \times Undercap_i * LowRating_j + \gamma X_{i,09} + \eta_j + \eta_c + u_{i,c,j}, \tag{3.9}$$

where all variables are defined as before. All variables are weighted using the IPWs obtained in section 3.5. The results are shown in Panel B of Table 3.B.6. We classify borrowers as risky if their credit rating is BB or lower at the end of 2009 ($LowRating$).[31]

For reasons of brevity, we only report the coefficient on $Undercap$ and the interaction term. Consistent with Figure 3.A.4 above, we find that undercapitalized banks reduce lending to low-quality firms, which is reasonable as these loans c.p. need to be funded with more regulatory capital.

It is a testable hypothesis that undercapitalized banks were more likely to sustain lending to "zombie" firms, i.e. to extend loans to distressed firms at subsidized terms. We identify a firm to be a "zombie" firm ($Zombie$) if its rating is BB or lower and it pays interest on its loans that is below the benchmark interest of loans to very safe, publicly traded firms. To identify if a firm pays below-benchmark interest rates, we follow the approach of Acharya et al. [2019b]: we use information from Amadeus to derive a proxy for average interest payments by firm j. Amadeus reports total interest paid and total outstanding debt of firm j in industry s in year t. We calculate the average interest paid(r_j) by firm j by dividing the total interest payment by the total outstanding debt in 2009. Firms have a high (low) reliance on short-term debt if the ratio of short-term debt to long-term debt is above (below) the median.

We calculate the benchmark interest R as the median interest rate paid by publicly traded firms within the same industry j in 2009 that were incorporated in non-GIIPS countries and had an AAA or AA rating. This is done separately for firms with low and high reliance on short-term debt (as a proxy for the maturity structure of debt). A

[31] For many firms we do not observe an external rating. In those cases we construct a rating using a mapping table provided by Moody's and taking as input the interest coverage ratio and sector (cf. Acharya et al. [2019a]).

firm pays below-benchmark interest rates if the average interest paid on its debt r_j is below the benchmark R, with firms split according to their reliance on short-term debt. To test the change in lending to "zombie" firms, we estimate the cross-sectional WLS regressions interacting $Undercap$ with $Zombie$:

$$\Delta Loan_{09-12,i,c,j} = \beta_1 \times Undercap_i + \beta_2 \times Undercap_i * Zombie_j + \gamma X_{i,09} + \eta_j + \eta_c + u_{i,c,j}. \tag{3.10}$$

All variables are weighted using the inverse probability weights obtained in section 3.5. We report the results in Panel C of Table 3.B.6. Consistent with our hypothesis, we find that undercapitalized banks reduce lending to "non-zombie" firms relative to better-capitalized banks. However, they lend substantially more to "zombie" firms.

Lastly, to maximize their cost-return trade-off, undercapitalized banks could be incentivized to lend to riskier borrowers within a rating, and therefore regulatory risk weight and capital cost category, if it allows them to charge a higher interest rate. We term this "search-for-yield" lending, as banks seek to maximize the rent for the given cost, ignoring the (within-rating category) risk.

We investigate this hypothesis with the following regression:

$$\Delta Loan_{09-12,i,c,j} = \beta_1 \times Undercap_i + \beta_2 \times Undercap_i * LowRating_j + + \tag{3.11}$$

$$\beta_3 \times Undercap_i * HighIR_j + +\beta_4 \times Undercap_i * LowRating_j * HighIR_j + \tag{3.12}$$

$$\gamma X_{i,09} + \eta_j + \eta_c + u_{i,c,j}, \tag{3.13}$$

where $HighIR_j$ is defined as a dummy which equals 1 if a firm pays interest rates above the average in its industry in 2009. Since higher interest rates are paid by riskier borrowers, we additionally interact this dummy with the low rating indicator from before to identify variations within this risky borrower class. The results in Panel D of Table 3.B.6 show some indication in favor of the hypothesis without being particularly robust.

3.7.2 Extensive vs. intensive margin

We also measure changes in loan supply at the extensive margin. First, to capture the propensity to maintain lending to a relationship borrower, we construct the indicator variable $Relationship_{i,c,j}$ that takes value 1 if bank i has lent to firm j in the year 2009 and therefore had a standing relationship entering the period of investigation, and 0 otherwise. Bank–firm relationships with no lending exposure in 2009, respectively a relationship value of 0, are then excluded from these regressions. Second, to capture a bank's willingness to enter a new lending relationship, we use as a dependent variable the product of the logarithm of the exposure and indicator $NewLoan_{i,c,j}$ that takes value 1 if bank i has a strictly positive (new) exposure to firm j in 2012 and 0 otherwise.

The results of the extensive and intensive margin regressions for aggregate lending decisions, estimated with WLS, are presented in Panel A of Table 3.B.7. We document a significant effect in both the subsample for relationship borrowers and the subsample of new borrowers, i.e. undercapitalized banks decreased lending to customers across the board.

When turning to the subset of risky borrowers, interestingly, we do not find a significant effect for relationship loans (Table 3.B.7, Panel B). A possible interpretation is that undercapitalized banks continue lending to lower-rated, particularly "zombie" firms, to avoid writing these loans off and further eroding their capital.

[Table 3.B.7 about here]

Consistent with the interpretation of "zombie" lending as effectively evergreening of existing loans to distressed firms, we find such an effect particularly in the subsample of relationship customers (Table 3.B.7, Panel C, column 1), but not the subsample of new relationships, where the coefficient is actually negative even though statistically insignificant (Table 3.B.7, Panel C, column 2). This is intuitive, as banks would not want to engage in a new lending relationship with a firm that is close to default.

We provide robustness tests with respect to our model specification. In Panels C to F of Table 3.B.11, we show that the lending results described above are robust to using a different weighting scheme. The coefficients hardly change. Using no weight, and therefore treating the undercapitalization status as exogenous, weakens the results distinctively. It appears that the endogeneity associated with the classification of being undercapitalized would bias the results for the model at hand. Hence, it proves important to use the reweighting scheme to obtain more credible parameter estimates, in particular regarding the micro-level lending behavior of undercapitalized banks.

3.7.3 Real effects

We want to substantiate our claim that continued lending to the firms we identified as ″zombies″ is in fact evergreening, as opposed to banks using their informational advantage to provide loans to firms that are in a solid economic state but, for example, suffer from a short-term liquidity problem. To this end, Table 3.B.8 gives a comparison of ″zombie″ firms that undercapitalized banks are lending to, compared to ″zombie″ firms that better-capitalized banks are lending to. In the years 2010 to 2012, i.e. in the period where the lending was documented, the ″zombie″ firms matched with undercapitalized banks performed considerably worse. Their return on assets is lower and their EBITDA over total assets is significantly lower, as is their cash flow over total assets. Moreover, similar to the ″zombie″ firms in Acharya et al. [2019b], our ″zombie″ firms have higher leverage but lower cash, even though they are roughly of the same size. All in all, we clearly document that the economic situation of ″zombie″ firms matched with undercapitalized banks would not warrant loans to such preferential interest rates, especially because it further seems that they could pledge less collateral as their tangibility ratio is lower than that of their peers.

Lastly, revisiting the hypothesis about ″search-for-yield lending″, we turn to Panel D in Table 3.B.7. While we have strong significance in the relationship lending column, it is important to note that the parameter estimates almost cancel each other out, implying that there is no economically meaningful effect to be found. In the new lending segment, however, we observe a statistically significant coefficient with large economic magnitude. While undercapitalized banks lend less to high-risk borrowers per se (negative double interaction), they cut lending less to those risky borrowers who pay a higher interest rate (positive triple interaction). The results thus show strong evidence in favor of ″search-for-yield lending″ behavior by undercapitalized banks.[32]

3.8 Undercapitalization and portfolio composition

As a final channel of impact of being left undercapitalized, we investigate the portfolio composition of affected banks. As we pointed out above, undercapitalized banks engage in serious efforts to improve their capital position, both regulatory by lending less to risky borrowers, and economically by stalling the write-off of ″zombie″ loans. A

[32]Similar behavior has been documented in Jiménez et al. [2017].

further way to reach this goal available to European banks is holding government debt issued by European sovereigns, as the risk weights are set to 0 by the regulator for these exposures.

For the purpose of investigating this channel, we first take a look at the change of the securities-to-loans ratio of the banks in our sample from 2009 to 2012 by running an analogous WLS regression to the one in Section 3.6. The results are displayed in column 1 of Table 3.B.9. The coefficient for the undercapitalization indicator is sizeable and highly significant: undercapitalized banks increased their securities-to-loans ratio significantly compared to their better-capitalized peers.

To get a better feel for the economic magnitudes, see Figure 3.A.5. Better-capitalized banks increased their loan-to-assets ratio by 2 p.p. and the securities-to-assets ratio by 0.25 p.p. on average. Undercapitalized banks, on the other hand, decreased their loans-to-assets ratio by 1 p.p. and increased their securities-to-assets ratio by 5.5 p.p. from 2009 to 2012.

[Figure 3.A.5 about here]

In order to understand in greater detail which securities were bought by the undercapitalized banks, we use the EBA's stress test data providing information on government debt holdings at the bank level. The results, estimated via WLS, for examining the change to the domestic government debt holdings, as well as the GIIPS government debt holdings, as a proxy for risky government debt, are displayed in columns 2 and 3 of Table 3.B.9. We document that undercapitalized banks increased both their domestic and their GIIPS government bond holdings significantly. To see to what extent the results in column 3 are driven by GIIPS banks, where the GIIPS bonds are domestic bonds, we split the results in column 3 by including a GIIPS dummy showing that undercapitalized banks across the board increased their GIIPS government bond holdings significantly, but banks located in GIIPS countries did it even more.[33]

[Table 3.B.9 about here]

Figure 3.A.6 helps in dissecting the time line of the government bond purchases by undercapitalized banks in our sample during the years 2010 to 2012. While in 2010 undercapitalized banks seemed not to be buying considerably more government debt than better-capitalized banks, the picture changes starkly in 2011.[34] Undercapitalized banks

[33] As before, we show robustness of the results using alternative weighting schemes in Panel F of Figure 3.B.11.

[34] The shaded red area depicts the 95% confidence interval.

now increased their load on GIIPS government bonds by 5.5 p.p relative to their better-capitalized peers. This gap opened even further in 2012, reaching values of around 7.75 p.p. This time line suggests that banks did not immediately shift to government bonds by the mere fact of leaving the crisis undercapitalized (2009 and 2010). Instead, sovereign yields first had to rise considerably to make it an attractive business, especially in the light of zero risk weights.

[Figure 3.A.6 about here]

Altogether, we see that banks not only optimized their economic and regulatory capital ratios by cutting back lending to risky borrowers and evergreening loans to "zombie" firms, but also by massive purchases of zero risk weight government bonds during the European sovereign debt crisis. This behavior kick-started the diabolic bank-sovereign loop, as documented by Acharya et al. [2014] and others.

3.9 Conclusion

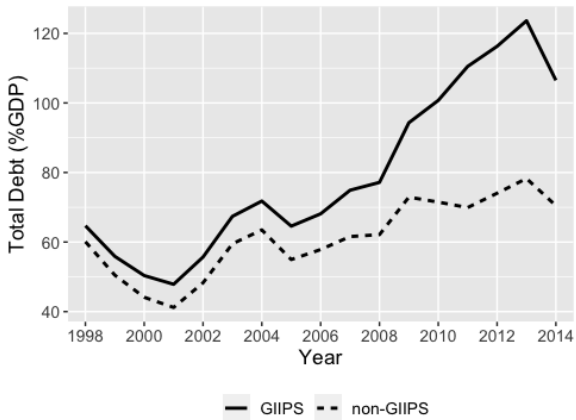
We analyzed the consequences of distressed banking sectors being left undercapitalized by fiscally stretched European governments during the GFC. Despite the increasingly cross-border nature of the European banking sector, recapitalizations of distressed banks were closely tied to the fiscal capacity of the domestic sovereign that was also responsible for its supervision. In the absence of an insolvency regime for banks, governments with lower fiscal capacity were effectively practicing forbearance instead of implementing fully fledged recapitalizations. Such "kicking the can down the road" left distressed banking sectors vulnerable to future economic shocks which materialized post-2009, and led to evergreening of loans to poor-quality borrowers by insufficiently stabilized banks as well as a shift from real sector lending to risky government bond holdings by such banks.

Consequently, our analysis informs the debate about the future design of the eurozone banking sector and the desirable institutional framework to underpin it. In particular, our results highlight the importance of reducing the dependence between the health of eurozone banks and the immediate sovereigns both in terms of decision-making processes for bank support and also at the fiscal level so as to minimize the possibility for forbearance in the future. The more that supervision and resolution of banks becomes shielded from the discretionary decision-making of national governments, the lower will be the opportunity for governments to resort to forbearance. By centralizing the supervision of banks with the ECB under the Single Supervisory Mechanism and by establishing the Single Resolution Mechanism as a common, standardized resolution scheme, the eurozone has made an important step towards resolving these interlinkages. However, an additional necessary ingredient for reducing forbearance is a common European fiscal backstop for recapitalization of the financial sector. To minimize moral hazard at the sovereign level, such fiscal backstops could be accompanied by strong rules for public finances, macroeconomic stability, and pre-arranged fiscal burden sharing.

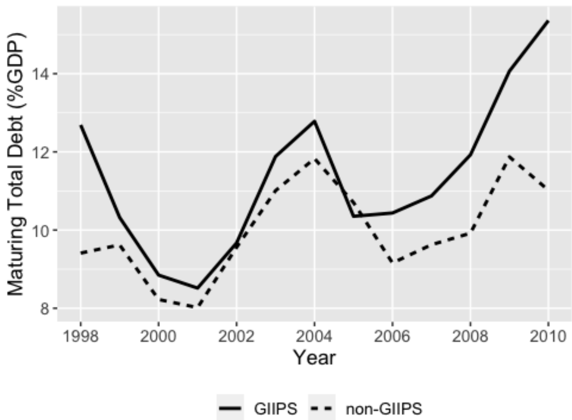
Appendix

3.A Figures

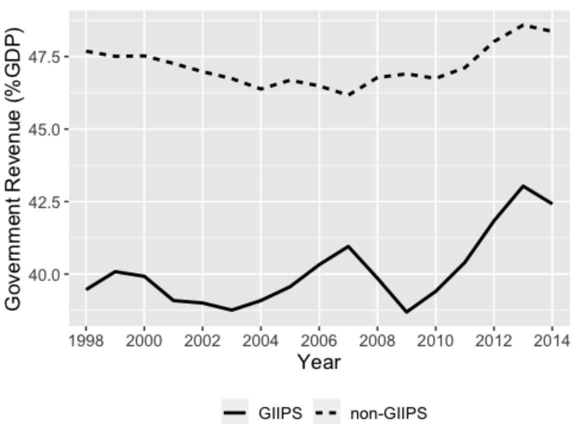
Figure 3.A.1: Developments of fiscal capacity: GIIPS vs non-GIIPS countries



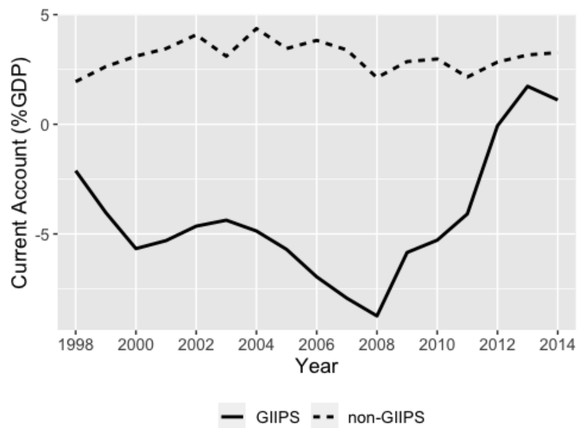
a) Total Debt



b) Maturing Debt



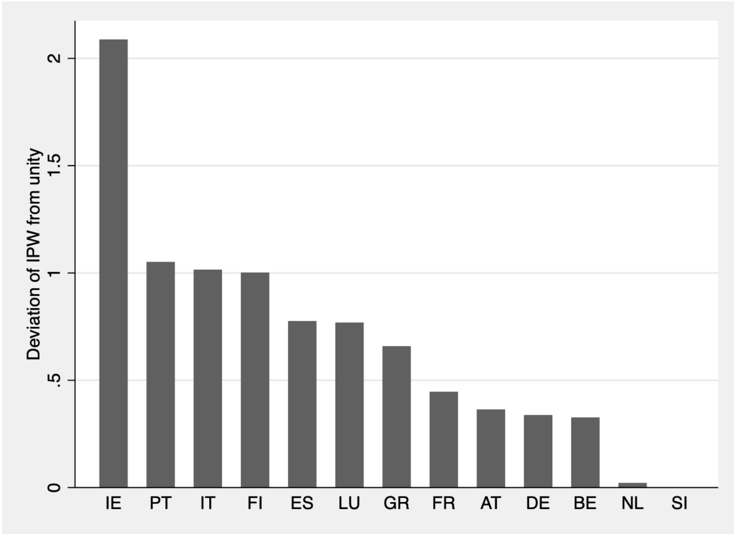
c) Government Revenues



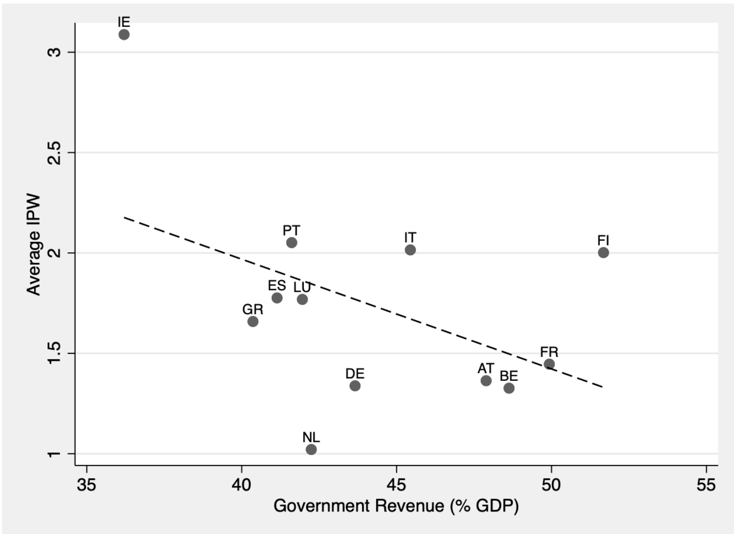
d) Current Account

Sources: IMF, OECD, World Bank.
Notes: GIIPS refers to Greece, Ireland, Italy, Portugal, and Spain, while non-GIIPS refers to Eurozone countries other than GIIPS.

Figure 3.A.2: Inverse Probability Weights (IPW): Descriptives



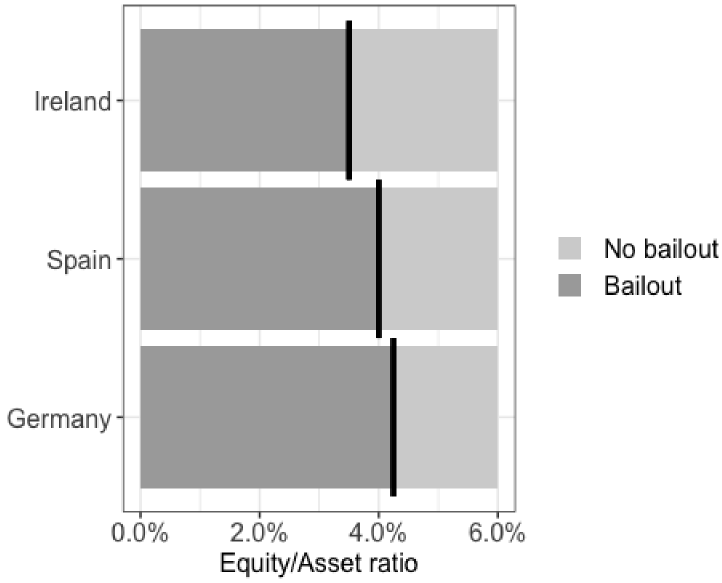
a) Deviation of IPW from unity per country ("randomness")



b) Scatterplot of average IPW vs. government revenue at the country level

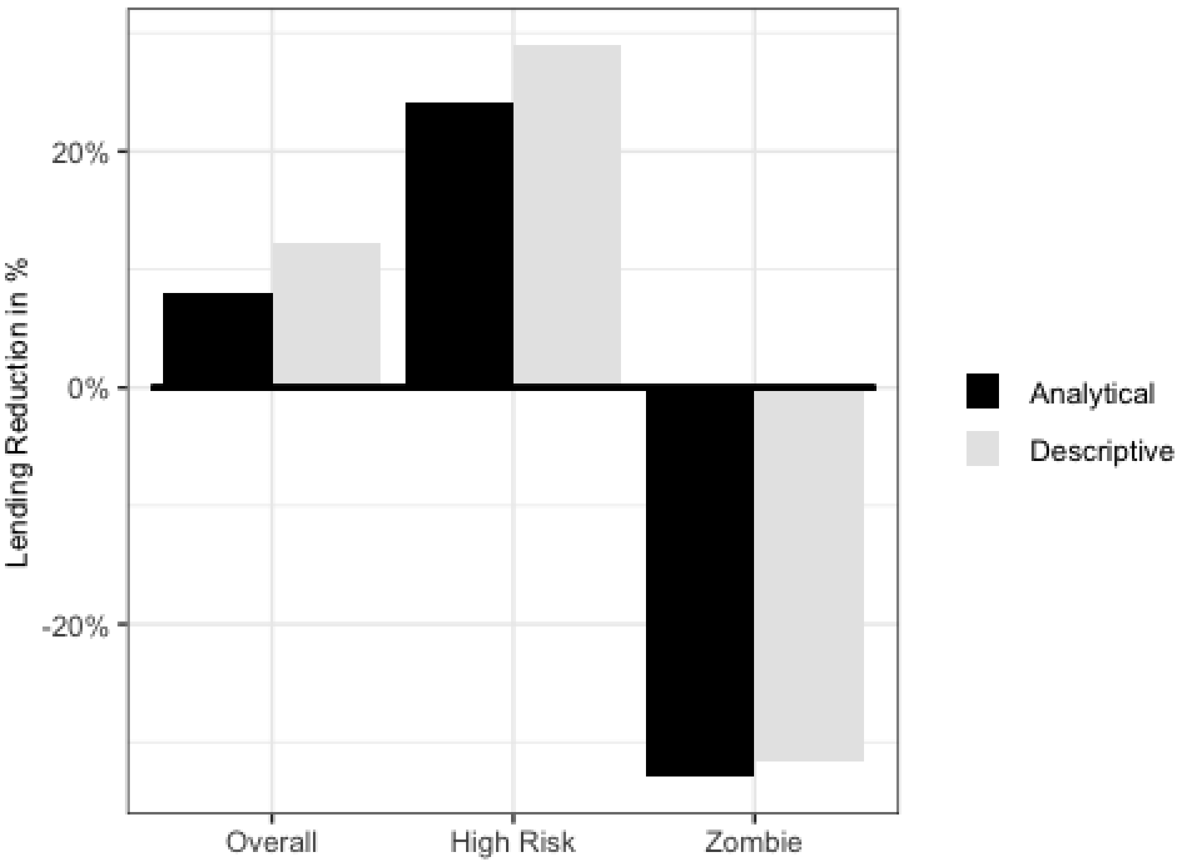
Notes: AT = Austria, BE = Belgium, DE = Germany, ES = Spain, FI = Finland, FR = France, GR = Greece, IE = Ireland, IT = Italy, LU = Luxembourg, NL = Netherlands, PT = Portugal, SI = Slovenia.

Figure 3.A.3: Stylized Depiction of Endogeneity in Recapitalizations



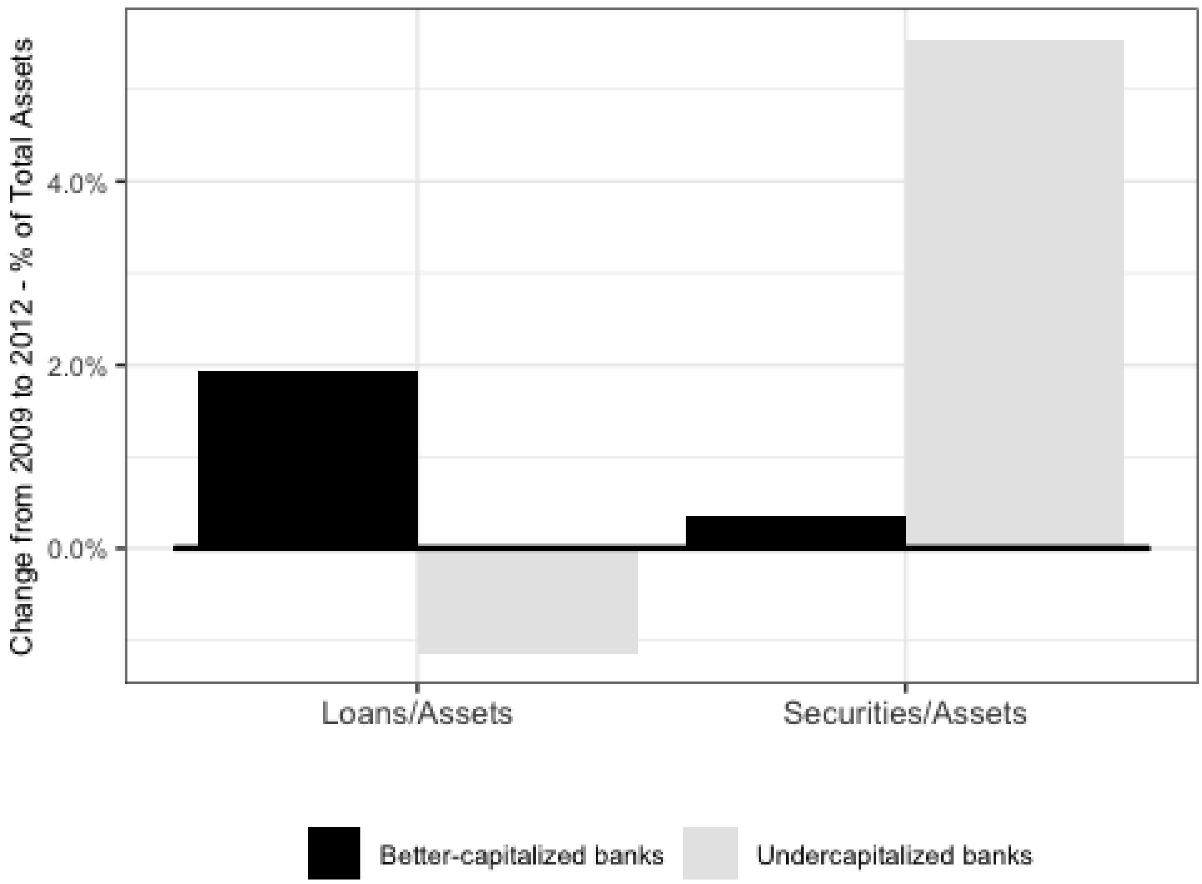
This graph shows a stylized depiction of how recapitalization ("bailout") of banks depends on the national government. Germany could afford to bailout banks with higher equity-to-asset ratio than Spain and Ireland. Our statistical approach allows us to eliminate this endogeneity, while ignoring this induces estimation bias.

Figure 3.A.4: Excess Reduction in Lending by Undercapitalized Banks relative to Better-capitalized Ones



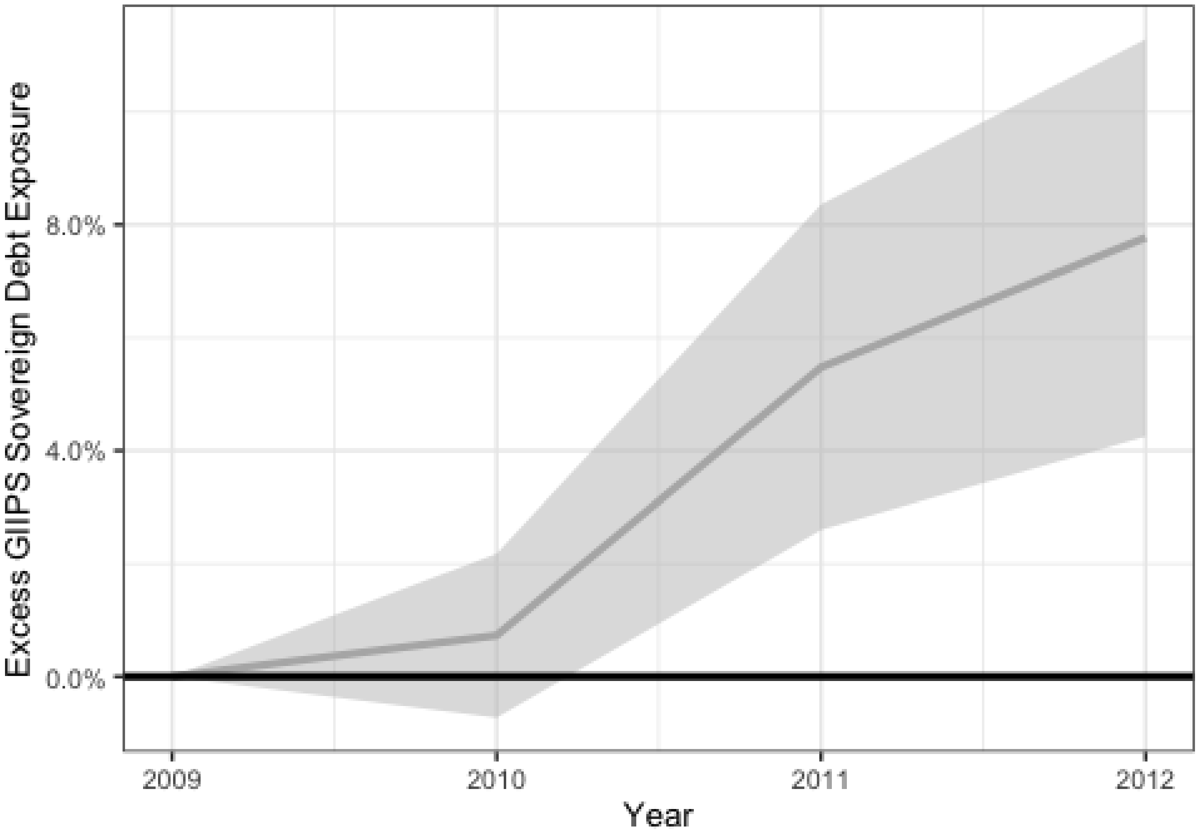
This graph shows the difference between the reduction in lending between undercapitalized and better-capitalized banks (”excess reduction”). Positive values refer to negative loan growth, and vice versa. ”Analytical” refers to the coefficient estimates from the regression models in Section 3.7. ”Descriptive” refers to the purely descriptive difference between the lending reductions in the sample. ”Overall”, ”High Risk”, and ”Zombie” are all as defined in Section 3.7.

Figure 3.A.5: Evolution of Loans-to-Assets and Securities-to-Assets Ratio for Undercapitalized Banks relative to Better-capitalized Ones



This graph shows the descriptive differences between the gross loans-to-assets ratio and the debt securities-to-assets ratio at the end of 2012 compared to the end of 2009 on banks' balance sheets.

Figure 3.A.6: Evolution of GIIPS government Debt Exposure relative to 2009 for Undercapitalized Banks relative to Better-capitalized Ones



This graph shows the evolution of the divergence of GIIPS government bond purchases between undercapitalized banks and better-capitalized banks ("excess exposure"). Normalizing the outstanding exposure in 2009 to 1, the graph shows by how much more the GIIPS sovereign debt exposure has risen per year for undercapitalized banks compared to better-capitalized banks.

3.B Tables

Table 3.B.1: Variable Definitions and Summary Statistics

The table shows variable definitions and summary statistics for government aid (Panel A), bank-level (Panel B) and macro-level (Panel C) variables. All bank-level and macro-level variables are as of end-2007.

Panel A: Government aid

VARIABLES	Definition	N	Mean	Median	SD	Min	Max
All Aid	Banks that received any type government aid between 2007 and 2009	84					
Recap	Banks that received a recapitalization between 2007 and 2009 (descriptives refer to amounts in % of total assets)	35	2.19	1.23	3.17	0.19	16.77

Panel B: Bank-level variables

VARIABLES	Definition	N	Mean	Median	SD	Min	Max
Total Assets/GDP	Total assets to nominal GDP (%)	830	3.46	0.13	13.33	0.04	128.72
Log Loans	Log gross loans	826	7.83	7.38	1.52	5.53	13.23
Loans/TA	Gross loans to total assets (%)	826	60.91	62.64	18.63	3.16	95.39
Net Int. Margin	Net interest margin (% of total assets)	825	2.19	2.25	0.82	0.13	4.03
Equity/TA	Total equity to total assets (%)	830	6.51	6.03	2.75	0.01	19.76
Tier 1 Ratio	Tier 1 regulatory capital ratio (%)	280	9.42	8.45	3.32	4.51	24.13
LLP/Loans	Loan loss provisions to gross loans (%)	806	0.71	0.54	1.38	-1.29	34.14
NPLs/Loans	Non-performing loans to gross loans (%)	262	3.53	2.72	4.35	0.18	42.58
Log Age	Log time since incorporation	319	3.97	4.41	1.15	0.69	7.50
ROAA	Return on average assets (%)	827	0.51	0.29	0.63	-1.40	7.41
ST funding/TA	Short-term funding to total assets (%). Short-term funding is calculated as Bankscope Global Item 'Deposits & Short-Term Funding' less Bankscope Universal Item 'Total Deposits'.	811	0.97	0.00	3.80	-0.10	47.89
Loans/Deposits	Loans to deposits (%)	799	117.84	99.88	74.72	22.36	598.73
Log z-score	Log z-score (Laeven and Levine [2009])	721	4.72	4.62	1.27	0.74	7.36
RWA/TA	Risk-weighted assets to total assets (%)	259	67.40	72.70	20.48	10.42	95.37
Securities/TA	Securities to total assets (%)	826	20.83	18.73	14.25	0.05	99.74

Panel C: Macro-level variables

VARIABLES	Definition	N	Mean	Median	SD	Min	Max
Government Revenue	Government revenues (% of nominal GDP)	13	44.16	43.36	4.36	36.20	51.68
Total Debt	Total debt (% of nominal GDP)	13	55.69	63.66	30.77	7.71	103.10
Maturing Debt	Maturing government debt (% of nominal GDP)	13	10.10	11.49	5.06	1.22	18.09
Current Account	Current account balance (% of nominal GDP)	13	-0.95	-0.33	7.35	-14.00	9.92
Avg. Equity Ratio	Banking sector average of 'Equity/TA'	13	6.88	6.83	1.38	4.11	9.07
Avg. Tier 1 Ratio	Banking sector average of 'Tier 1 Ratio'	12	9.35	9.28	1.87	6.41	12.10
Log time to election	Logarithm of time until next election	12	6.72	7.06	0.70	5.23	7.35
Anti/Pro EU	Anti/Pro EU scale of government (0–10)	13	1.82	0.56	2.64	0	8.76

Table 3.B.2: Baseline Cox Regression for Government Interventions

The table presents the results of Cox regressions for government interventions between September 15, 2008 and December 31, 2009. Banks exit the sample if they receive a government intervention of any type (*any*) or a recapitalization (*recap*). Hazard rates $h_{AID},\ AID \in \{any, recap\}$ take the exponential form:

$$h_{AID,i}(t) = h_{AID,0}(t) \cdot \exp(\beta_0 \times X_{i,t-1} + \beta_1 \times b_{c,t-1} + \beta_2 \times m_{c,t-1}).$$

Bank-level variables $X_{i,t-1}$ comprise total assets to domestic GDP (*Total Assets/GDP*), the equity-to-assets ratio (*Equity/TA*), the short-term funding ratio (*ST funding/TA*) and return on average assets (*ROAA*). Banking sector variables $b_{c,t-1}$ comprise the average equity ratio in the domestic banking sector (*Average Equity Ratio*) and the number of banks that already received recapitalization (*Banks with recaps*). Macroeconomic variables $m_{c,t-1}$ comprise the government revenues to GDP (*Government Revenue*), the maturing government debt to GDP (*Maturing Debt*), the current account balance (*CA Balance*), the total government debt to GDP (*Debt/GDP*), real GDP growth (*GDP growth*), GDP per capita ((*GDP*), and household debt over GDP (*HH Debt/GDP*) in the respective country as well as a the logarithm of the time until the next election (*Log Time to Election*). Lastly, we add a control for the pro, respectively anti, EU sentiment in the current government (*Pro EU*). Control variables are not displayed in the table. Tie-breaking follows the Efron rule. Standard errors are robust and adjusted for clustering at the country level. The table reports coefficient estimates. Parentheses contain p-values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. $NFail$ is the number of hazard events, i.e. the number of government interventions of the respective type. The estimation sample contains 832 banks.

Panel A - Recapitalization

VARIABLES	(1)	(2)	(3)	(4)
Government Revenue (%GDP)	0.23***	0.27***	0.22***	0.25***
	(0.00)	(0.00)	(0.00)	(0.00)
Debt/GDP	-0.02			0.05**
	(0.47)			(0.04)
Maturing Debt (%GDP)		-0.23***		-0.43***
		(0.00)		(0.00)
CA Balance			0.03	0.11**
			(0.68)	(0.02)
Observations	18,826	18,826	18,826	18,826
N fail	32	32	32	32
Pseudo-R2	0.39	0.40	0.39	0.40

Panel B - Any aid

VARIABLES	(1)	(2)	(3)	(4)
Government Revenue (%GDP)	-0.03	-0.02	0.01	0.01
	(0.80)	(0.87)	(0.95)	(0.94)
Debt/GDP	-0.01			-0.02
	(0.74)			(0.33)
Maturing Debt (%GDP)		-0.04		0.09
		(0.79)		(0.55)
CA Balance			-0.07	-0.10
			(0.44)	(0.27)
Observations	41,234	41,234	41,234	41,234
N fail	76	76	76	76
Pseudo-R2	0.23	0.23	0.23	0.23
Cluster	country	country	country	country
Tie-break	Efron	Efron	Efron	Efron

Table 3.B.3: Descriptive Statistics of the Sample of Banks by Capitalization

The table shows the number of banks that are classified as undercapitalized and/or which received aid as well as their split across countries.

Panel A - Any aid vs. recapitalization vs. no aid

	Undercapitalized banks	Better-capitalized banks	Total
Received aid	13	71	84
Received recap.	8	27	35
Received no aid	68	678	746
Total	81	749	830

Panel B - Capitalization status of banking sector by country

Country	Number of undercapitalized banks	Number of better-capitalized banks	Number of banks (total)	Share of undercapitalized banks
NL	0	19	19	0.00%
FR	1	25	26	3.85%
DE	18	437	455	3.96%
BE	1	13	14	7.14%
PT	1	9	10	10.00%
ES	10	69	79	12.66%
AT	6	35	41	14.63%
FI	1	5	6	16.67%
GR	2	10	12	16.67%
LU	1	4	5	20.00%
IT	35	110	145	24.14%
SI	2	6	8	25.00%
IE	3	7	10	30.00%

Notes: AT = Austria, BE = Belgium, DE = Germany, ES = Spain, FI = Finland, FR = France, GR = Greece, IE = Ireland, IT = Italy, LU = Luxembourg, NL = Netherlands, PT = Portugal, SI = Slovenia.

Table 3.B.4: Likelihood of a Bank being Undercapitalized

The table presents the results of a logit regression with the following specification:

$$Undercap_i = \frac{exp(\beta X_i)}{1 + (exp(\beta X_i)} \text{ where } \beta X_i = \beta_0 \times X_{i,2007} + \beta_1 \times b_{c,2007} + \beta_2 \times m_{c,2007} + \beta_3 \times X_{i,2007} * m_{c,2007}.$$

The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. Bank-level variables $X_{i,2007}$ comprise total assets to domestic GDP (*Total Assets/GDP*), the equity-to-assets ratio (*Equity/TA*), the short-term funding ratio (*ST funding/TA*) and return on average assets (*ROAA*), as of end-2007. Banking sector variables $b_{c,2007}$ comprise the average equity ratio in the domestic banking sector (*Average Equity Ratio*) and the number of banks that already received recapitalization (*Banks with recaps*). Macroeconomic variables $m_{c,2007}$ comprise the government revenues to GDP (*Government Revenue*), the maturing government debt to GDP (*Maturing Debt*), the current account balance (*CA Balance*), the total government debt to GDP (*Debt/GDP*), real GDP growth (*GDP growth*), GDP per capita ((*GDP*) and household debt over GDP (*HH Debt/GDP*) in the respective country as well as a the logarithm of the time until the next election (*Log Time to Election*). Lastly, we add a control for the pro, respectively anti, EU sentiment in the current government (*Pro EU*). Control variables are not displayed in the table. All non-binary variables are demeaned. Standard errors are robust and adjusted for clustering at the country level. The table reports coefficient estimates. Parentheses contain p-values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Government Revenue (%GDP)	-0.13	-0.12	0.19	0.23**
	(0.58)	(0.14)	(0.18)	(0.04)
Government Revenue (%GDP) × Total Assets/GDP	-0.03***	-0.03***	-0.01	-0.04**
	(0.00)	(0.00)	(0.10)	(0.02)
Government Revenue (%GDP) × Equity/Total Assets	-0.09**	-0.11*	0.07*	0.02
	(0.04)	(0.08)	(0.05)	(0.57)
Government Revenue (%GDP) × ROAA	0.21	0.25	-0.16	-0.11
	(0.11)	(0.24)	(0.34)	(0.30)
Debt/GDP	-0.00			-0.04
	(0.97)			(0.19)
Debt/GDP × Total Assets/GDP	0.00			-0.01
	(0.19)			(0.24)
Debt/GDP × Equity/Total Assets	0.02**			-0.02***
	(0.03)			(0.00)
Debt/GDP × ROAA	-0.04**			-0.25**
	(0.02)			(0.04)
Maturing Debt (%GDP)		14.88*		60.63***
		(0.10)		(0.00)
Maturing Debt (%GDP) × Total Assets/GDP		1.43*		6.89**
		(0.08)		(0.01)
Maturing Debt (%GDP) × Equity/Total Assets		9.03**		18.16***
		(0.03)		(0.00)
Maturing Debt (%GDP) × ROAA		-16.96*		129.98*
		(0.08)		(0.07)
Current Account			-0.26	-0.53***
			(0.20)	(0.00)
Current Account × Total Assets/GDP			-0.00	-0.02**
			(0.55)	(0.05)
Current Account × Equity/Total Assets			-0.07***	-0.12***
			(0.00)	(0.00)
Current Account × ROAA			0.19***	-0.12
			(0.00)	(0.38)
Observations	781	781	781	781
Cluster	country	country	country	country

Table 3.B.5: Impact of being Undercapitalized on Banks' Balance Sheet and Sovereign Crisis Outcomes

Panel A of the table displays results from a weighted-least squares (WLS) regression of changes in balance sheet characteristics from 2009 to 2012 on the undercapitalization status and a set of control variables. The weighting scheme is obtained from running the regression in Table 3.B.4, column 2:

$$\Delta Y_{i,09-12} = \alpha + \beta \times Undercap_i + \gamma \times X_{i,2009} + u_i.$$

Panel B of the table displays results from a weighted-least squares (WLS) regression of bank-level outcomes during the sovereign debt crisis (2010–2013) on the undercapitalization status and a set of control variables. The weighting scheme is the same as above:

$$Y_i = \alpha + \beta \times Undercap_i + \gamma \times X_{i,2009} + v_i.$$

The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. Bank-level variables $X_{i,2009}$ comprise total assets to domestic GDP (*Total Assets/GDP*), the equity-to-assets ratio (*Equity/TA*), the loans-to-deposits ratio (*Loans/Deposits*) and return on average assets (*ROAA*), as of end-2009. $\Delta Y_{i,09-12}$ is the change from end-of-year 2009 to end-of-year 2012 for one of the following variables: equity-to-assets ratio (*Equity*), Tier 1 capital ratio (*Tier1*), total loans (*Loans*), loan loss provisions over loans (*LLP*), non-performing loans over loans (*NPL*), return on average assets (*ROAA*), net interest margin (*NIM*), risk-weighted assets over total assets (*RWA/TA*). Standard errors are robust and adjusted for clustering at the bank level. The table reports coefficient estimates. Parentheses contain p-values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A - Balance-sheet outcomes

VARIABLES	(1) $\Delta Equity_{09-12}$	(2) $\Delta Tier1_{09-12}$	(3) $\Delta Loans_{09-12}$	(4) ΔLLP_{09-12}	(5) ΔNPL_{09-12}	(6) $\Delta ROAA_{09-12}$	(7) ΔNIM_{09-12}	(8) $\Delta RWA/TA_{09-12}$
Constant	1.02***	0.70**	0.19***	-1.71***	0.27	1.33***	0.27***	-0.16
	(0.00)	(0.05)	(0.00)	(0.00)	(0.47)	(0.00)	(0.00)	(0.27)
Log Total Assets	-0.05***	-0.03	-0.00	0.06*	-0.00	-0.09**	-0.02**	0.01
	(0.00)	(0.23)	(0.73)	(0.08)	(0.88)	(0.05)	(0.02)	(0.53)
Equity/Total Assets	-0.06***	-0.05***	-0.01**	0.09***	-0.00	-0.08***	-0.02**	0.01
	(0.00)	(0.00)	(0.01)	(0.00)	(0.82)	(0.01)	(0.02)	(0.28)
ROAA	-0.04	0.09*	-0.03	0.69***	0.13	-0.81***	-0.04	-0.03
	(0.30)	(0.07)	(0.16)	(0.00)	(0.12)	(0.00)	(0.17)	(0.54)
Loans/Deposits	-0.00	0.00	-0.00***	0.00	0.00***	0.00	0.00	-0.00
	(0.68)	(0.63)	(0.00)	(0.16)	(0.00)	(0.74)	(0.94)	(0.23)
Undercap	-0.09**	0.21**	-0.04*	0.74***	-0.06	-0.19	-0.04	0.02
	(0.01)	(0.03)	(0.05)	(0.00)	(0.48)	(0.13)	(0.27)	(0.84)
Observations	649	261	651	439	184	554	651	210
R-squared	0.30	0.10	0.15	0.27	0.11	0.20	0.06	0.03
Cluster	bank	bank	bank	bank	bank	bank	bank	bank

Panel B - Sovereign-crisis outcomes

VARIABLES	(1) Recap 2010–13	(2) Survival until 2012	(3) LTRO Uptake/TA
Constant	-11.03***	3.70***	48.24**
	(0.00)	(0.00)	(0.02)
Log Total Assets	0.71***	-0.25**	-1.83**
	(0.00)	(0.03)	(0.03)
Equity/Total Assets	0.08	0.06	-2.67**
	(0.25)	(0.40)	(0.05)
ROAA	-0.43***	0.63***	9.32***
	(0.00)	(0.01)	(0.00)
Loans/Deposits	0.00	0.00	-0.02
	(0.19)	(0.69)	(0.53)
Undercap	0.08	-0.18	12.06**
	(0.92)	(0.64)	(0.01)
Observations	736	736	57
(Pseudo) R-squared	0.35	0.26	0.37
Cluster	bank	bank	bank

Table 3.B.6: Impact of being Undercapitalized on Banks' Lending Behavior – Overall

Panel A of the table presents the results of cross-sectional Khwaja and Mian (2008)-type bank lending regressions based on syndicated loan data and estimated with weighted-least squares (WLS):

$$\Delta y_{2009-12,i,c,j} = \beta \times Undercap_i + \gamma' X_{i,2009} + \eta_j + \eta_c + u_{ijc}.$$

Panels B, C and D present the results of identical regressions with the indicator for undercapitalization interacted with dummies for "high-risk", "zombie" or high-interest-paying firms as defined in the main text.
The unit of observation is at the bank-firm level. $y_{2009-12,i,c,j}$ measures the change in loan supply in the 2009 to 2012 period and is defined in the text. The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. The weighting scheme is obtained from running the regression in Table 3.B.4, column 2. Bank-level control variables $X_{i,2009}$ comprise log total assets (*Log Total Assets*), the equity-to-assets ratio (*Equity/Tot Assets*), the return on average assets (*ROAA*), and the non-performing loans to loans ratio (*NPL*), as of end-2009. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. FE denotes fixed effects. IR stands for paid interest rate.

VARIABLES	(1) Δ Loan	(2) Δ Log Loan	(3) Loan Increase
	Panel A - aggregate lending		
Undercap	-0.14***	-0.21***	-0.04**
	(0.01)	(0.01)	(0.05)
Observations	19,943	19,943	19,943
R-squared	0.79	0.75	0.75
	Panel B - risky lending		
Undercap	0.05	0.07	0.01
	(0.60)	(0.68)	(0.74)
Undercap × Low Rating	-0.30**	-0.43**	-0.12**
	(0.03)	(0.01)	(0.01)
Observations	3,423	3,423	3,423
R-squared	0.71	0.64	0.67
	Panel C - zombie lending		
Undercap	-0.14**	-0.21**	-0.04
	(0.03)	(0.02)	(0.17)
Undercap × Zombie	0.36**	0.40*	0.07
	(0.01)	(0.06)	(0.14)
Observations	3,293	3,293	3,293
R-squared	0.73	0.68	0.69
	Panel D - rent-seeking lending		
Undercap	0.39*	0.27	0.22**
	(0.09)	(0.35)	(0.03)
Undercap × Low Rating	-0.46**	-0.52*	-0.38***
	(0.02)	(0.10)	(0.01)
Undercap × High IR	-0.43*	-0.36	-0.30**
	(0.10)	(0.24)	(0.01)
Undercap × Low Rating × High IR	0.25	0.26	0.38**
	(0.29)	(0.49)	(0.04)
Observations	2,931	2,931	2,931
R-squared	0.72	0.66	0.68
Cluster	bank	bank	bank
Firm FE	YES	YES	YES
Country FE	YES	YES	YES
Controls	YES	YES	YES

Table 3.B.7: Impact of being Undercapitalized on Lending Behavior – Intensive vs. Extensive Margin

Panel A of the table presents the results of cross-sectional Khwaja and Mian (2008)-type bank lending regressions based on syndicated loan data and estimated with weighted-least squares (WLS):

$$\Delta y_{2009-12,i,c,j} = \beta \times Undercap_i + \gamma' X_{i,2009} + \eta_j + \eta_c + u_{ijc}.$$

Panels B, C and D of the table present the results of identical regressions with the indicator for undercapitalization interacted with dummies for "high-risk", "zombie" or high-interest-paying firms as defined in the main text.
$y_{2009-12,i,c,j}$ measures the change in loan supply at the extensive or intensive margin in the 2009 to 2012 period and is defined in the text. The unit of observation is at the bank-firm level. The weighting scheme is obtained from running the regression in Table 3.B.4, column 2. The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. Bank-level control variables $X_{i,2009}$ comprise log total assets (*Log Total Assets*), the equity-to-assets ratio (*Equity/Tot Assets*), the return on average assets (*ROAA*), and the non-performing loans to loans ratio (*NPL*), as of end-2009. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. FE denotes fixed effects. IR stands for paid interest rate.

VARIABLES	(1) Relationship borrowers	(2) New borrowers
Panel A - aggregate lending		
Undercap	-0.08**	-0.20***
	(0.01)	(0.00)
Observations	14,411	4,891
R-squared	0.74	0.90
Panel B - risky lending		
Undercap	0.05	0.09
	(0.51)	(0.49)
Undercap × Low Rating	-0.24	-0.21
	(0.10)	(0.41)
Observations	2,371	891
R-squared	0.68	0.89
Panel C - zombie lending		
Undercap	-0.05	0.05
	(0.33)	(0.66)
Undercap × Zombie	0.33**	-0.24
	(0.03)	(0.15)
Observations	2,205	950
R-squared	0.69	0.90
Panel D - rent-seeking lending		
Undercap	0.48**	0.16
	(0.01)	(0.19)
Undercap × Low Rating	-0.65***	-0.69**
	(0.00)	(0.05)
Undercap × High IR	-0.54**	-0.14
	(0.02)	(0.46)
Undercap × Low Rating × High IR	0.56***	1.06***
	(0.01)	(0.01)
Observations	1,997	796
R-squared	0.70	0.89
Cluster	bank	bank
Firm FE	YES	YES
Country FE	YES	YES
Controls	YES	YES

Table 3.B.8: Descriptive Statistics of "Zombie" Firms

The table compares some descriptive statistics of zombie firms borrowing from undercapitalized banks with zombie firms borrowing from better-capitalized banks. The displayed values in Panel A are means of the variables in the year 2009. The displayed values in Panel B are means of the variables in the years 2013 to 2016. The last column shows the p-values of a t-test for differences in means.

Panel A: as of 2009			
VARIABLES	Borrowing from undercapitalized banks	Borrowing from better-capitalized banks	p-value of t-test
Interest Coverage Ratio	-2.78	1.94	0.07
EBITDA/Total Assets	0.03	0.03	0.80
ROA	-1.01	0.63	0.25
Cash Flow/Total Assets	0.02	0.03	0.47
Sales/Assets	0.14	0.62	0.00
Tangible Assets/Total Assets	0.98	0.92	0.00
Cash/Total Assets	0.07	0.05	0.53
Liabilities/Total Assets	0.70	0.80	0.02
Log Total Assets	18.96	19.32	0.38
Panel B: as of 2013–2016			
VARIABLES	Borrowing from undercapitalized banks	Borrowing from better-capitalized banks	p-value of t-test
Interest Coverage Ratio	-1.87	14.06	0.00
EBITDA/Total Assets	0.03	0.05	0.05
ROA	-1.16	1.51	0.00
Cash Flow/Total Assets	0.02	0.06	0.00
Sales/Assets	0.30	0.72	0.00
Tangible Assets/Total Assets	0.72	0.88	0.00
Cash/Total Assets	0.04	0.06	0.00
Liabilities/Total Assets	0.81	0.69	0.00
Log Total Assets	19.47	19.68	0.22

Table 3.B.9: Impact of being Undercapitalized on Banks' Portfolio Composition

The table displays results from a weighted-least squares (WLS) regression of changes in asset holdings from 2009 to 2012 on the undercapitalization status and a set of control variables. The weighting scheme is obtained from running the regression in Table 3.B.4, column 2:

$$\Delta Y_{i,09-12} = \beta \times X_{i,2009} + \alpha \times Undercap_i.$$

The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. Bank-level variables $X_{i,2009}$ comprise log total assets (*Log Total Assets*), the equity-to-assets ratio (*Equity/TA*), the NPL-to-loans ratio (*NPL/Loans*) and return on average assets (*ROAA*), as of end-2009. $\Delta Y_{i,09-12}$ is the change from end-of-year 2009 to end-of-year 2012 for one of the following variables: the security-to-loan ratio (*Securities/Loans*), the domestic sovereign bond holdings (*GovBonds Domestic*), and the holdings of sovereign bonds issued by GIIPS countries (*GovBonds GIIPS*). Standard errors are robust and adjusted for clustering at the bank level. The table reports coefficient estimates. Parentheses contain p-values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) ΔSecurities/ Loans$_{09-12}$	(2) ΔGovBonds Domestic$_{09-12}$	(3) ΔGovBonds GIIPS$_{09-12}$	(4) ΔGovBonds GIIPS$_{09-12}$
Constant	0.00	-0.07	1.50	-0.29
	(0.99)	(0.95)	(0.43)	(0.81)
Log Total Assets	0.01	0.06	-0.10	0.02
	(0.81)	(0.50)	(0.44)	(0.85)
Equity/Total Assets	0.03	-0.05	-0.08	-0.13**
	(0.25)	(0.31)	(0.29)	(0.02)
ROAA	0.21*	-0.07	0.06	-0.07
	(0.08)	(0.60)	(0.80)	(0.69)
NPLs/Loans	-0.01	-0.08**	-0.02	-0.01
	(0.54)	(0.02)	(0.42)	(0.67)
Undercap	0.44***	0.95***	1.11***	0.76**
	(0.00)	(0.01)	(0.00)	(0.02)
GIIPS Bank				1.03***
				(0.00)
Observations	189	39	38	38
R-squared	0.14	0.38	0.31	0.62
Cluster	bank	bank	bank	bank

Table 3.B.10: Likelihood of a Bank being Undercapitalized – Robustness

The table presents the results of a logit regression with the following specification:

$$Undercap_i = \frac{exp(\beta X_i)}{1 + (exp(\beta X_i)} \text{ where } \beta X_i = \beta_0 \times X_{i,2006} + \beta_1 \times b_{c,2006} + \beta_2 \times m_{c,2006} + \beta_3 \times X_{i,2006} * m_{c,2006}.$$

The variable *Undercap* takes the value 1 if a bank is classified as undercapitalized as defined in the text. Bank-level variables $X_{i,2006}$ comprise total assets to domestic GDP (*Total Assets/GDP*), the equity-to-assets ratio (*Equity/TA*), the short-term funding ratio (*ST funding/TA*) and return on average assets (*ROAA*), as of end-2006. Banking sector variables $b_{c,2006}$ comprise the average equity ratio in the domestic banking sector (*Average Equity Ratio*) and the number of banks that already received recapitalization (*Banks with recaps*). Macroeconomic variables $m_{c,2006}$ comprise the government revenues to GDP (*Government Revenue*), the maturing government debt to GDP (*Maturing Debt*), the current account balance (*CA Balance*), the total government debt to GDP (*Debt/GDP*), real GDP growth (*GDP growth*), GDP per capita ((*GDP*) and household debt over GDP (*HH Debt/GDP*) in the respective country as well as a the logarithm of the time until the next election (*Log Time to Election*). Lastly, we add a control for the pro, respectively anti, EU sentiment in the current government (*Pro EU*). Control variables are not displayed in the table. All non-binary variables are demeaned. Standard errors are robust and adjusted for clustering at the country level. The table reports coefficient estimates. Parentheses contain p-values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
Government Revenue (%GDP)	-0.37**	-0.32*	0.13	0.34**
	(0.05)	(0.09)	(0.53)	(0.02)
Government Revenue (%GDP) × Total Assets/GDP	-0.02**	-0.02***	-0.02*	-0.04**
	(0.01)	(0.00)	(0.08)	(0.02)
Government Revenue (%GDP) × Equity/Total Assets	-0.08	-0.09	0.09***	0.11***
	(0.27)	(0.18)	(0.00)	(0.00)
Government Revenue (%GDP) × ROAA	0.03	0.08	-0.49**	-0.56**
	(0.84)	(0.54)	(0.03)	(0.02)
Debt/GDP	-0.03**			-0.21***
	(0.04)			(0.00)
Debt/GDP × Total Assets/GDP	0.00			-0.01*
	(0.25)			(0.09)
Debt/GDP × Equity/Total Assets	0.02*			-0.04**
	(0.09)			(0.02)
Debt/GDP × ROAA	-0.05*			-0.06
	(0.07)			(0.12)
Maturing Debt (%GDP)		-1.00		110.81***
		(0.92)		(0.00)
Maturing Debt (%GDP) × Total Assets/GDP		0.64		8.71**
		(0.35)		(0.03)
Maturing Debt (%GDP) × Equity/Total Assets		7.38		26.78***
		(0.13)		(0.00)
Maturing Debt (%GDP) × ROAA		-17.69*		19.54
		(0.08)		(0.24)
Current Account			-0.29*	-0.74***
			(0.06)	(0.00)
Current Account × Total Assets/GDP			-0.00	-0.02**
			(0.92)	(0.04)
Current Account × Equity/Total Assets			-0.11***	-0.16***
			(0.00)	(0.00)
Current Account × ROAA			0.38***	0.32***
			(0.00)	(0.00)
Observations	766	766	766	766
Cluster	country	country	country	country

Table 3.B.11: Impact of being Undercapitalized on Various Measures – Alternative Weights

The table presents the results of re-running the weighted-least squares (WLS) specifications from Tables 3.B.5 to 3.B.9 with alternative weighting schemes. The weights are obtained from Table 3.B.10, column 2, or are all set to 1, respectively. Standard errors are clustered at the bank level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A - Balance-sheet variables

VARIABLES	(1) $\Delta Equity_{09-12}$	(2) $\Delta Tier1_{09-12}$	(3) $\Delta Loans_{09-12}$	(4) ΔLLP_{09-12}	(5) ΔNPL_{09-12}	(6) $\Delta ROAA_{09-12}$	(7) ΔNIM_{09-12}	(8) $\Delta RWA/TA_{09-12}$
				Panel A.1 - weights from Table 3.B.10, column 2				
Undercap	-0.10***	0.22*	-0.04	0.72***	-0.00	-0.13	-0.02	0.03
	(0.01)	(0.07)	(0.11)	(0.00)	(0.98)	(0.31)	(0.55)	(0.75)
Observations	608	247	610	417	177	519	610	199
R-squared	0.30	0.08	0.17	0.27	0.10	0.25	0.08	0.05
				Panel A.2 - no weight				
Undercap	-0.13***	0.18*	-0.05**	0.79***	-0.04	-0.10	-0.07	-0.05
	(0.00)	(0.09)	(0.03)	(0.00)	(0.58)	(0.56)	(0.13)	(0.39)
Observations	669	271	671	456	198	564	671	219
R-squared	0.25	0.08	0.13	0.23	0.04	0.16	0.03	0.06

Panel B - Sovereign-crisis performance

VARIABLES	(1) Recap 2010-13	(2) Survival until 2012	(3) LTRO Uptake/TA
		Panel B.1 - weights from Table 3.B.10, column 2	
Undercap	0.05	-0.33	11.83**
	(0.94)	(0.40)	(0.01)
Observations	689	689	56
R-squared	0.35	0.26	0.36
		Panel B.2 - no weight	
Undercap	0.57	-0.40	9.45**
	(0.28)	(0.24)	(0.03)
Observations	758	758	62
R-squared	0.33	0.25	0.29

Panel C - Aggregate lending

VARIABLES	(1) Δ Loan	(2) Δ Log Loan	(3) Loan Increase	(4) Relationship borrowers	(5) New borrowers
			Panel C.1 - weights from Table 3.B.10, column 2		
Undercap	-0.15**	-0.23**	-0.04**	-0.08**	-0.19***
	(0.01)	(0.01)	(0.05)	(0.05)	(0.00)
Observations	19,632	19,632	19,632	14,169	4,822
R-squared	0.79	0.74	0.75	0.74	0.90
			Panel C.2 - no weight		
Undercap	-0.10	-0.18*	-0.02	-0.05	-0.17***
	(0.13)	(0.08)	(0.40)	(0.25)	(0.00)
Observations	20,152	20,152	20,152	14,542	4,961
R-squared	0.78	0.74	0.75	0.73	0.89

Panel D - Risky lending

VARIABLES	(1) Δ Loan	(2) Δ Log Loan	(3) Loan Increase	(4) Relationship borrowers	(5) New borrowers
			Panel D.1 - weights from Table 3.B.10, column 2		
Undercap	0.03	0.04	0.00	0.04	0.08
	(0.79)	(0.83)	(0.98)	(0.66)	(0.55)
Undercap × Low Rating	-0.28**	-0.39**	-0.11**	-0.21	-0.16
	(0.04)	(0.02)	(0.01)	(0.13)	(0.50)
Observations	2,748	2,748	2,748	2,330	296
R-squared	0.67	0.59	0.62	0.66	0.95
			Panel D.2 - no weight		
Undercap	-0.00	0.08	0.01	0.03	0.14
	(0.99)	(0.70)	(0.77)	(0.72)	(0.33)
Undercap × Low Rating	-0.14	-0.32*	-0.09**	-0.11	-0.07
	(0.24)	(0.07)	(0.05)	(0.41)	(0.81)
Observations	3,458	3,458	3,458	2,392	905
R-squared	0.69	0.62	0.66	0.66	0.89

Panel E - Zombie lending

VARIABLES	(1) Δ Loan	(2) Δ Log Loan	(3) Loan Increase	(4) Relationship borrowers	(5) New borrowers
			Panel E.1 - weights from Table 3.B.10, column 2		
Undercap	-0.14*	-0.19*	-0.05	-0.06	0.05
	(0.05)	(0.07)	(0.12)	(0.32)	(0.66)
Undercap × Zombie	0.35**	0.35	0.07	0.33**	-0.23
	(0.03)	(0.12)	(0.13)	(0.04)	(0.15)
Observations	2,579	2,579	2,579	2,166	306
R-squared	0.70	0.64	0.64	0.69	0.96
			Panel E.2 - no weight		
Undercap	-0.12	-0.16	-0.04	-0.04	0.11
	(0.13)	(0.17)	(0.26)	(0.49)	(0.36)
Undercap × Zombie	0.31	0.23	0.11**	0.27	-0.37*
	(0.11)	(0.37)	(0.03)	(0.12)	(0.05)
Observations	3,314	3,314	3,314	2,218	959
R-squared	0.72	0.66	0.68	0.67	0.90

Panel F - Rent-seeking lending

VARIABLES	(1) Δ Loan	(2) Δ Log Loan	(3) Loan Increase	(4) Relationship borrowers	(5) New borrowers
			Panel F.1 - weights from Table 3.B.10, column 2		
Undercap	0.34	0.24	0.18*	0.44**	0.14
	(0.13)	(0.43)	(0.05)	(0.02)	(0.25)
Undercap × Low Rating	-0.42**	-0.47	-0.34**	-0.64***	-0.64*
	(0.02)	(0.14)	(0.01)	(0.00)	(0.07)
Undercap × High IR	-0.39	-0.33	-0.27**	-0.50**	-0.12
	(0.12)	(0.29)	(0.02)	(0.02)	(0.50)
Undercap × Low Rating × High IR	0.21	0.22	0.34**	0.58***	1.02***
	(0.40)	(0.58)	(0.04)	(0.01)	(0.01)
Observations	2,883	2,883	2,883	1,959	786
R-squared	0.71	0.65	0.67	0.68	0.89
			Panel F.2 - no weight		
Undercap	0.06	0.15	0.13	0.14	0.16
	(0.78)	(0.63)	(0.17)	(0.42)	(0.16)
Undercap × Low Rating	-0.14	-0.24	-0.21*	-0.30	-0.51
	(0.52)	(0.45)	(0.08)	(0.19)	(0.30)
Undercap × High IR	-0.11	-0.20	-0.19*	-0.13	-0.07
	(0.63)	(0.53)	(0.10)	(0.56)	(0.71)
Undercap × Low Rating × High IR	0.07	0.05	0.20	0.28	0.80
	(0.80)	(0.90)	(0.21)	(0.29)	(0.12)
Observations	2,957	2,957	2,957	2,014	806
R-squared	0.70	0.64	0.67	0.68	0.89

Panel G - Sovereign debt

VARIABLES	(1) ΔSecurities/ Loans$_{09-12}$	(2) ΔGovBonds Domestic$_{09-12}$	(3) ΔGovBonds GIIPS$_{09-12}$	(4) ΔGovBonds GIIPS$_{09-12}$
		Panel G.1 - weights from Table 3.B.10, column 2		
Undercap	0.49***	0.92**	1.06***	0.73**
	(0.00)	(0.01)	(0.01)	(0.03)
GIIPS Bank				1.07***
				(0.00)
Observations	180	38	37	37
R-squared	0.16	0.37	0.35	0.62
		Panel G.2 - no weight		
Undercap	0.40***	0.89**	0.69	-0.97**
	(0.00)	(0.02)	(0.17)	(0.02)
GIIPS Bank				1.15***
				(0.00)
Undercap × GIIPS				1.54***
				(0.00)
Observations	208	41	39	39
R-squared	0.08	0.26	0.05	0.62

Chapter 4

Clear(ed) decision: the implications of central clearing for firms' financing decision

Joint with Frederick Zadow (University of Mannheim).

4.1 Introduction

As a response to the Great Financial Crisis (GFC), regulatory authorities around the globe have passed an array of new laws with the aim of improving the resilience of the global financial system. One major incision to derivative markets was the promotion of central clearing (CC) through central counterparties (CCPs). That is, derivative trades are not only cleared through a clearing house by settling payments, but the clearing house actively takes on the counterparty risk against both trading partners. As a consequence of this regulatory push, the share of centrally cleared derivatives has substantially increased over the last decade (see Figures 4.A.2 and 4.A.3).[1] Clearly, a regulatory change of this magnitude has implications beyond its narrowly defined intended target – financial stability. In particular, it seems likely that there are (potentially unintended) consequences for the real economy as the reform affects financial intermediaries and their capital allocation decisions with implications for firm capital structure and investment. In this paper, we ask what are the consequences for a firm if its CDS contract – an

[1] These reforms and their efficacy are evaluated in Financial Stability Board [2018].

insurance contract against its default – is available for central clearing? Broad changes to the market environment (risk structure, trading costs, etc.) of such an insurance product, provoked by the CCP reforms, could significantly affect investors' demand for CDS and corporate bonds and thus the firm's capital structure and performance.

To tackle this question empirically we use a staggered difference-in-differences setup. Our setting is the CDS market for US firms in the years 2012 – 2019. To identify the impact of CC, we exploit the fact that clearing is not mandatory for single name corporate CDS contracts. Instead, the monopolistic clearing entity decides on the eligibility of firms[2] in a time-staggered fashion.[3] We jointly exploit this cross-sectional and temporal variation to estimate the effect of CC eligibility on firm-level variables. One possible threat to our identification strategy is the potential endogeneity in the eligibility decision by the monopolist CCP. A for-profit CCP should make firms whose CDS contract is in high demand eligible for clearing to maximize profits. This demand could correlate with, e.g., higher risk of default because more investors want to buy insurance, biasing our results. Using a propensity-score matching approach controlling for firm-level balance-sheet and financial soundness factors, we address this issue to come closer to identifying the average causal effect on treated firms.

We find that the lower counterparty risk on centrally cleared CDS contracts incentivizes investors who operate in both markets to transfer capital from the bond to the CDS market. Firms try to compensate for this loss in bond demand by demanding more bank loans. Because banks do not supply sufficient credit, however, firms lose external financing. That is, central clearing stimulates a less than one-to-one substitution in the debt composition between bonds and loans. We further document that this has adverse consequences for the affected firms as they cut investment and turn less profitable.

We start with documenting that in the three trading weeks following the announcement of clearing eligibility, the CDS spreads of affected firms rise significantly by more than 2.5%. Since this effect could be market-specific, as the reform directly targets CDS contracts, we further investigate the stock market reaction around the announcement. Our results show that stock valuations drop significantly and persistently by 1.5% in the

[2]Throughout this paper we will speak of the "eligibility of a firm" when we refer to the eligibility of the CDS contracts which specify the firm as the reference entity.

[3]Due to regulatory incentives for banks who act as market makers this decision immediately leads to a strong shift of the trading activities for the eligible firms' CDS to the centrally cleared market segment.

event window. That is, markets did not fully anticipate the clearing decisions, highlighting the success of our matching strategy. Moreover, markets perceive clearing eligibility as a meaningful and adverse event for the real economic outlook of affected firms.
But how exactly are firms affected? We build a parsimonious model which incorporates both corporate bond and CDS markets to postulate two distinct economic channels through which the CDS market environment can affect firm bond demand.
Central counterparties are complex entities particularly designed to be the center piece of a large trading network. Their main mechanism is to split contracts between investor A and B into two, one between investor A and the CCP and one between investor B and the CCP – the so-called novation of contracts. This allows the CCP to take on the counterparty risk for all players in the market, thereby minimizing contagion risks. To fulfil this task and absorb potential losses, the CCP is equipped with several lines of defense: initial and variation margins, default fund contribution (all of which can be subsumed under collateral), and its own equity capital built up by making profits and collecting fees. For a more elaborate treatment of CCPs and their history, please see Appendix 4.A.
Notwithstanding their complex nature, our model will focus on the two most salient features for investors provoked by the introduction of CC in the CDS market: i) the decrease in counterparty default risk, and ii) the increase in trading costs (collateral, fees).[4] This allows us to propose two channels through which firms' bond demand can be affected.

We start from the model put forward by Oehmke and Zawadowski [2015]. In this framework, there exists a corporate bond of a single firm that stochastically defaults. Additionally, there is a CDS contract available that pays out the bond's face value in case of the firm's default. The model is populated by a continuum of investors that differ along two dimensions: their belief about the default risk of the firm and the risk of liquidity shock occurrence forcing them to liquidate their position before maturity. The differential beliefs generate a trading motive, while the differential liquidity risk ensures that some investors prefer the CDS market over the bond market since the former is assumed to incur smaller trading costs, respectively be more liquid.

[4]Our analysis is not restricted to a decrease in counterparty default risk and an increase in trading costs. Our calibration exercise shows, however, that the data is only consistent with these directions of change. Since they are both the intuitive *and* the empirically documented directions, we favor this language, despite our results being general.

On top of the Oehmke and Zawadowski [2015] framework, we introduce counterparty default risk on the derivative market. That is, if the firm defaults, there is a non-zero probability that investors holding the CDS contract will not be paid out the insurance. The main regulatory aim of the introduction of central clearing was to mitigate this counterparty default risk.[5] Such a risk mitigation does not come for free, however. Investors incur higher trading costs on a centrally cleared market by the means of collateral requirements, default fund contributions or trading fees[6], potentially deterring them. We investigate the equilibrium effects of lower counterparty risk and higher trading costs both separately and jointly.

We propose two channels of effect. First, the decrease in counterparty risk raises the attractiveness of CDS contracts because a payout becomes more likely. This mechanically increases the price. Due to the higher price, it becomes more attractive for investors to sell CDS contracts. Some (marginal) investors will therefore sell CDS contracts instead of buying corporate bonds – two alternatives that otherwise exhibit the same risk profile and similar cash flows. As a result, the demand for firms' CDS contracts increases and the demand for bonds decreases. We term the changes induced by lower counterparty risk the *arbitrage channel*, as the no-arbitrage condition between the two markets gets shifted, inducing traders to leave the bond, and enter the CDS market. Second, higher CDS trading costs induce investors – both from the buy and sell side – to leave the CDS market and to switch to either buying bonds or holding cash. Since former CDS sellers have two alternatives (holding cash and buying bonds), but former CDS buyers only have one (holding cash), there are more sellers than buyers leaving the CDS market. This is because former CDS sellers believe in the survival of the firm, but former CDS buyers do not. Hence, the latter are not interested in buying the bond. These investor flows create an upward pressure on the CDS price. As some CDS sellers become bond buyers, there is upward pressure on the bond price as well. The rise in both bond and CDS prices leads fewer people to conduct the hedged trade of jointly buying the bond and the CDS contract. In sum, CDS prices go up while CDS demand goes down. The effect on bond demand is ambiguous due to fewer people conducting the hedged trade. We term this effect the *hedging channel* as its relevance depends on the existence of investors with a hedged position.

[5]See, e.g., Cecchetti et al. [2009].

[6]See, e.g., Biais et al. [2012], Biais et al. [2016], Kuong and Maurin [2021].

Taken together, both channels imply a rise in the CDS price. However, the predictions with respect to the outstanding CDS volume and with respect to bond outcomes differ.

As a natural next step, we test whether we can detect the arbitrage and hedging channel in the data. To link the theoretically described channels to empirical estimates, we need concepts that represent the quantities and prices for bonds, and the quantities and prices for CDS contracts. The quantity of bonds is measured by total outstanding bond debt of the firms such that the demand can be inferred from jointly analyzing quantities and prices which we measure with yields. The quantity of CDS contracts is measured by the outstanding notional (i.e., the total insurance sum) for a firm, while the price of CDS contracts is measured by the CDS spread.

Our diff-in-diff results show that CDS spreads are, on average, 20 basis points higher for eligible firms, confirming the unambiguous model prediction of higher prices. Bond supply is significantly reduced, with the volume of outstanding bond debt dropping by 2.2%. At the same time, yields rise slightly albeit not being statistically significant. This suggests that demand had to be substantially lower to allow for market clearing at lower quantities and stable prices. Thus, firms in our sample adjust their corporate debt supply instead of letting market prices move too heavily.

Furthermore, our results indicate that the outstanding notional for eligible firms is not moving significantly. The demand for CDS contracts is therefore higher to achieve market clearing at higher prices and stable quantities. These results are consistent with the move from investors from the bond to the CDS market – the arbitrage channel. That is, the arbitrage channel dominates the hedging channel.[7]

We further analyze data about the bond and CDS holdings of mutual funds. Our results show that after eligibility of a firm, mutual funds decrease the holdings of its bonds compared to the holdings of bonds issued by firms in the control sample. Moreover, mutual funds increase their selling of CDS contracts written on eligible firms compared to CDS contracts written on firms in the control sample. This empirically confirms the very essence of the arbitrage channel for a specific class of investors: a decrease in bond demand and an increase in CDS selling.

[7]To better understand the relative strengths of the two channels, we link the empirical findings back to our model. We calibrate our model to the pre-event time window of our sample in terms of CDS and bond market characteristics. We then jointly simulate a reduction in the counterparty risk (driving the arbitrage channel) and an increase in the trading costs (driving the hedging channel). The changes in outcomes observed in the data prove to be consistent with a strong decrease in the counterparty risk (30-50%) and a small increase in trading costs (5-10%).

Given these effects on bond demand, one would expect firms to search for other forms of funding to mitigate the impact on their balance sheet. A natural candidate are loans from banks, as these are less closely related to CDS markets[8] and can be accessed on relatively short notice. We test this hypothesis using syndicated loan[9] data from Dealscan.

Using the same identification strategy as before we show that, indeed, bank credit increases after CC eligibility. Outstanding exposure increases by 3.4% of previous quarter total assets, relative to uncleared firms. Although supportive of our hypothesis, this result does not tell us whether firms actually increased their demand for bank loans. To distinguish between credit supply and demand we make use of the fact that, in our data set, banks lend to multiple firms. Following a variant of the approach of Khwaja and Mian [2008], we then employ a regression model with $bank \times time$ fixed effects which control for bank credit supply. We find that after CC eligibility, firms increase their demand for bank loans by around 4.3% of total assets. We interpret the larger coefficient of the second specification such that the increase in firms' credit demand was larger than the amount of credit extended to firms. That is, firms could not fully compensate their loss in debt funding. Lastly, we split the sample into term loans and credit lines. We show that the demand increase is mainly driven by credit lines, funding which can be accessed on short notice and is used to protect against liquidity shortages (Sufi [2009]).

If firms lose bond financing and banks only fill the gap insufficiently, what does this mean for firms' balance sheets? Balance sheet effects are economically sizeable with an average total debt reduction of 2.7%. Long-term debt (with a maturity of more than 1 year) is the main driver with a reduction of 2.9%, whereas short-term debt is not affected. The debt decrease is accompanied by a reduction in firm size (measured as total assets) of 1.6%, while equity is not significantly affected. Consistent with this finding, firms leverage is reduced by around 0.4 percentage points. Thus, firms shrink as a response to clearing eligibility relative to uncleared firms.[10]

To shed light on the real economic effects of the CCP reforms in a normative sense, we

[8] On the one hand, there is no obvious no-arbitrage condition between the two markets. On the other hand, banks do not engage in single name CDS trading to hedge their exposures (e.g. Caglio et al. [2019]).

[9] Syndicated loans are extended by a consortium of banks to a firm.

[10] The estimation horizon of these effects varies from three to five years due to the staggered structure of our data set. To better understand the dynamics of the effects, Section 4.6.3 contains event studies where we look at the impact at quarterly frequency. We find that the balance sheet responses take two to three years to build up.

investigate the impact of CC – and the resulting reduction of debt financing – on the performance of affected firms. We document that they have a return on assets that is 0.23 percentage points lower and that they suffer from a decrease in their stock price of around 3%. Moreover, affected firms reduce their capital stock, measured as plants, property and equipment by roughly 1.5 percentage points. These estimates are statistically and economically significant.[11] Firms seem to be forced to reduce their production inputs to balance operating expenses and cash-flows from debt financing. This is not a healthy shrinkage as profitability drops and the stock market reacts accordingly. Thus, we document a trade-off between financial stability and real economic activity to be inherent to the CCP reform.

The concurrency of our rich set of evidence makes other channels of explanation less likely than the postulated arbitrage channel. For example, one might be concerned that CCPs have superior information about the future trajectory of firms and select firms which they identified as being on a downward trend. Given a high accuracy in CCPs' prediction, this would explain why firms perform worse after eligibility and investors reduce their bond demand as a consequence. One might also wonder if there is an adverse signalling effect of being chosen for central clearing. This would explain the stock market reaction around the announcement and the decrease in bond demand. Neither of these explanations would be consistent, however, with banks increasing their credit supply to firms (at the same interest rate) and with mutual funds selling CDS contracts which is a bet on the survival of the firm.

Literature. Despite its importance, surprisingly, almost no one has traced the impact of CC's structural shift in the market structure of derivatives beyond derivative markets, to the best of our knowledge.[12] We fill this gap.

There has been extensive research on the design of CC as well as the asset pricing and, in particular, the market microstructure impact of CC of derivative contracts. Du et al. [2019] examine trade repository data for the over-the-counter CDS market and detect counterparty risk associated inefficiencies that a CCP could be able to resolve. As in our empirical setup, Loon and Zhong [2014] use the staggered eligibility for CC of

[11] Estimates for the number of employees are negative and economically meaningful, but not statistically significant.

[12] Vuillemey [2020], as a noteable exception, takes a historical perspective on the real economic implications of central clearing by examining the coffee futures market in Le Havre in the 1880s.

CDS contracts to causally identify its effects on the CDS market in the US. The authors find that CDS spreads increase around the introduction of CC and that trading activity as well as liquidity improve for eligible contracts.
There is a rich (theoretical) literature regarding the optimal design (Biais et al. [2012]; Biais et al. [2016]; Huang [2019]; Kessler [2021]; others) and the efficiency (Duffie and Zhu [2011]; Duffie et al. [2015]; others) of CCPs. Despite its broad implementation after the GFC, this literature advises caution in praising CC as the solution to financial stability and market efficiency concerns. We add empirical evidence to this literature that effects of central clearing are not only ambiguous from a financial stability point of view, but also from a real economic perspective when considering its impact beyond the derivative markets.

Additionally, we tie into the strand of literature concerned with the impact of CDS contracts on the quantity and composition of corporate debt. Duffee and Zhou [2001] theoretically motivates the positive externalities of hedging instruments for credit supply. Ashcraft and Santos [2009] show that the introduction of the CDS market itself did not significantly affect the cost of corporate debt, on average. Saretto and Tookes [2013], however, show that a traded CDS contract allows firms to increase leverage and debt maturities.[13]
A set of theoretical papers connecting the CDS and corporate debt markets also shows the relevance of market design and instrument properties for corporate finance. Oehmke and Zawadowski [2015] show that in the presence of liquidity advantages in the CDS market, investors might switch from buying bonds to selling CDS contracts (the essence of the 'arbitrage channel' in this paper). Che and Sethi [2014] also highlight that in the presence of an attractive CDS market, the cost of borrowing for underlying firms can both shrink and increase depending on the nature of the investors buying the excess supply of contracts. Speculators drive the cost of borrowing up, while investors with insurable interest drive it down.[14]
Our paper adds a further piece of evidence that the structure of the CDS market does indeed affect corporate capital structure.

[13]Hirtle [2009] provides mixed evidence on the quantity of debt funding.
[14]For an excellent overview of the literature related to the asset pricing and corporate finance perspective of CDS markets, see Augustin et al. [2014].

Lastly, our paper links to research on the determinants of debt composition in corporate finance and financial flexibility, more broadly. Many seminal theoretical papers about optimal debt composition are built around information asymmetries and how (bank) monitoring or other forms of information production alleviate them (Diamond [1991]; Rajan [1992]; others). The early empirical evidence (Houston and James [1996]; Denis and Mihov [2003]; others) points out that high-level firm characteristics such as size or credit quality are the most important determinants in the choice of public vs. private debt. More recent studies, such as Vig [2013] or Gopalan et al. [2016], have shown that debt composition strongly depends on the broad financial market environment that firms operate in. This ties into the literature on financial flexibility which highlights that frictions on funding markets can hinder firms from choosing the debt composition that they identify as optimal (Graham and Harvey [2001]; Denis [2011]; others). We contribute further to this collection of evidence, by showing how changes to the credit derivative market environment lead to a less than one-to-one substitution of public debt for private debt.

Roadmap. The remainder of the paper is structured as follows: Section 4.2 presents our data and the empirical setup and Section 4.3 discusses our identification strategy. Section 4.4 then describes our model and postulates the economic channels before Section 4.5 empirically investigates the presence of the channels. Section 4.6 studies the effects on firms' bank loan demand, balance sheet and performance, before Section 4.7 concludes.

4.2 Empirical strategy

This section presents the data used as well as our regression setup which we employ to estimate the effects of central clearing.

4.2.1 Data

Firms do not become eligible for clearing all at once. Instead, the monopolistic (100% market share in the relevant submarket) CCP in the CDS market decides on the eligibility of treatment: IntercontinentalExchange Clear Credit (ICECC). The dates for clearing eligibility are retrieved from the ICECC website directly. We identify 98 firms which become eligible in our sample period (see Table 4.B.1 for a list of firms and Figure 4.B.1 for the distribution of clearing dates over time). We restrict our sample to firms cleared after the 1st of January of 2013. There are three main reasons for that: 1) we want to avoid any lingering remains from the financial crisis such as deleveraging which would affect the comparability of the pre- and post-treatment windows; 2) the CDS market was reformed by the so-called ”big bang” and the ”small bang” initiatives in the direct aftermath of the GFC.[15] We want to prevent any pollution of our estimates due to these structural changes; 3) the Dodd-Frank act gave market making banks preferential regulatory treatment of cleared derivatives as of 1st of January 2013. Hence, the incentive for market makers to move the firm to the cleared market segment after eligibility is much stronger in this time period than it was before.[16]

Our control sample consists of all firms in the S&P 1500 which have an actively traded 5-year CDS contract written on their debt and for which there is sufficient data. For our selected firms we obtain quarterly balance sheet information from Compustat. Additionally, we use CDS pricing data from Markit. From DTCC, we get publicly available information on the total and average number of clearing dealers, average daily notional and average trades per day by reference entity for a subset of firms.[17] For all available firms we get corporate bond trading data from the WRDS Bond return database.[18] This data is merged via the bonds' CUSIP with the Mergent FISD bond issue data. This corporate bond data set contains information on corporate bond yields, return, trading volumes, and other characteristics. To match corporate bonds to CDS we only include corporate bonds which are senior debt, dollar-denominated, and have a fixed interest coupon. We further use the CRSP Mutual Fund Portfolio Holdings data set which allows us to track the holdings of bonds and CDS contracts referencing the firms in our sample by the universe of mutual funds in the United States. Lastly, we obtain information on syndicated loans extended to the firms in our sample from Thomson Reuters Dealscan for the same period.

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[15] For further information on the ”big bang” and the ”small bang”, see, e.g., Augustin et al. [2014].

[16] ICECC started its business in 2009. However, clearing was not yet incentivized by the regulator in any way back then. In a robustness exercise we use all firms becoming eligible starting in January 2011. Almost all of our results uphold in this sample, while the point estimates are a bit smaller (see Tables 4.G.2 to 4.G.4).

[17] http://www.dtcc.com/repository-otc-data

[18] https://wrds-www.wharton.upenn.edu/pages/grid-items/wrds-bond-returns/

An overview of all the variables used in this paper, their definition and sources can be found in Table 4.B.2.

4.2.2 Estimation

To gauge the impact of eligibility for central clearing on various balance sheet and market outcomes, we estimate two types of panel models. The first is a staggered difference-in-differences (DiD) model:

$$y_{it} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \delta y_{i,t-1} + \alpha_i + \alpha_t + u_t, \tag{4.1}$$

where $\mathbf{1}(t \geq Eligibility_i)$ is an indicator function recording a one for a treated firm starting at the quarter of treatment, $\mathbf{x}_{i,t-1}$ contains lagged control variables at the firm-level, α_i is a firm-fixed effect, and α_t is a time-fixed effect. This regression compares the level of the outcome variable y before treatment with the level after treatment and therefore allows us to estimate an average treatment effect on the treated. The difference to a classic DiD setup is that firms receive the treatment at varying points in time whereas in the classic set up all firms would be treated at the same time.

The estimate obtained for θ in Equation 4.1 will only consistently measure the average treatment effect on the treated (ATT) under two conditions. First, there may be no heterogeneity in the size of treatment effects, in general. Second, there may be no difference in the treatment effects of a firm which is eligible for five years (treatment at the beginning of the sample) compared to a firm which is eligible for only two years (treatment at the end of the sample). Our results show that most effects level off after two years, and we have no economic rationale for a mitigation of our effects over time.

To more formally refute concerns about treatment heterogeneity, we apply the methodology laid out in De Chaisemartin and d'Haultfoeuille [2020]. The authors show that θ is equivalent to a weighted sum of all individual treatment effects. These weights can be negative, potentially biasing the estimate up to the point where the estimated sign differs from the actual treatment effect. We find that more than 99.9% of the weights in our setting are positive. In addition, the method of the authors shows that the standard deviation of ATTs must be implausibly high to be consistent with a data generating process (DGP) where all ATTs are actually of opposite sign compared to θ. A DGP where the average of ATTs is zero also requires an implausible high standard deviation in ATTs. This together alleviates concerns about treatment heterogeneity.

We employ a second approach to better understand the dynamics of the effects. We estimate event-study type regressions – an extension of the staggered DiD model:

$$
\begin{aligned}
y_{i,t} = &\sum_{j=-k}^{l} \theta_j \mathbf{1}(t + j = Eligibility_i) \\
&+ \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_t + before_t + after_t + u_{i,t},
\end{aligned} \tag{4.2}
$$

where $\mathbf{1}(t + j = Eligibility_i)$ is an indicator which equals one if firm i becomes eligible for clearing in period $t + j$. The set $\{\theta_j\}_{j=-k}^{l}$ is our main object of interest. It contains the impact coefficients of clearing eligibility from k quarters before until l quarters after the date of clearing eligibility. We normalize $\theta_t = 0$. $\mathbf{x}_{i,t-1}$ is a set of lagged firm specific controls. $before_t$ and $after_t$ are dummies for the time period before, respectively after, our event window. The fixed effects structure is as before. With this approach we exploit the temporal variation of the treatment to identify the impact coefficients, while controlling for all factors that could drive a wedge between the average observation of the LHS variable for two different points in time. In all our estimations we cluster standard errors at the firm level.[19]

4.3 Identification

Our identification strategy builds on three key institutional details. First, under the Dodd-Frank act only index CDS have a mandatory clearing requirement. For all other CDS, such as sovereign and corporate single-name contracts, central clearing is encouraged (e.g. through more lenient capital requirements) but not mandatory. For this reason, CCPs can determine which reference entities (such as countries or corporates) to clear. Second, the CCPs did not make reference entities eligible for clearing at the same point in time. Instead, there was a staggered introduction to central clearing across time. This allows us to control for potentially confounding events at the time of treat-

[19] As documented in Abadie et al. [2017], the appropriate clustering level depends on the interpretation of the research design. Our results are robust to no clustering or clustering at the firm $\times$ time level.

ment which cannot be controlled for in a setting in which all units get treated at the same time. Lastly, central clearing of corporate CDS contracts in the US is concentrated at only one CCP, namely ICECC . This monopolistic market structure allows us to estimate effects which are general to the whole market and not particular to a subset of cleared CDS contracts.

In our regressions, we use the temporal variation in clearing eligibility across firms to identify the effect of central clearing. A typical concern would be that the timing of treatment (becoming eligible for clearing) coincides with some other event that is driving the results and therefore produces spurious estimates. Since firms in our sample are treated at various points in time, and we can therefore control for time fixed effects, this is very unlikely. Hence, an omitted factor would have to highly correlate with the timing of clearing eligibility across firms and time. Second, we use propensity score matching to select firms for the control sample (see below). Since control firms are therefore very similar to the treated firms, any factor which has an effect on the treated firms would most likely also affect the control firms (except for clearing eligibility). For these two reasons we are highly confident that our results are only attributable to the eligibility for central clearing. We will inspect parallel trends both in terms of quarterly balance sheet data and daily market prices around the announcement dates later in the paper. There are no signs that the matched control group deviates from the treatment group in any measurable way in the pre-treatment period.

Are there firm characteristics that predict eligibility? From direct communication with ICECC we know that potential candidate firms for clearing eligibility can neither suggest themselves as candidates nor can they directly influence the selection process in any way. ICECC does not inform selected firms about its decision. Instead, reference entities become eligible for clearing when it is commercially viable for ICECC to do so. It therefore appears reasonable to assume that firm characteristics play a role. For example, CDS demand for more risky firms could be higher, making it more attractive to clear these derivatives. For causal identification, we need the decision to make a firm eligible for clearing (and therefore the underlying determinants at the time of the decisions) to be uncorrelated with the future development of our variables of interest at the firm level (e.g. outstanding debt, leverage, assets, and profitability), conditional on observables.

We formally test this by analyzing whether any firm-level balance sheet variable can predict clearing eligibility. For this purpose we run a logistic regression with the following latent variable form:

$$\mathbf{1}(Eligibility_i) = \begin{cases} 1, & \text{if } \beta \mathbf{x}_{i,\overline{2011-2012}} + u_i > 0, \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

where the latent variable of our logit model $\mathbf{1}(Eligibility_i)$ takes the value one if firm i gets treated during our sample and zero otherwise. The vector of predictive variables $\mathbf{x}_{i,\overline{2011-2012}}$ contains the following variables: cash, capital expenditures, revenues, return on assets, leverage, total assets, total debt. All those variables are measured as the average over the eight quarters from 2011Q1 until 2012Q4. This specification is the result of several iterations maximizing both the fit of the regression (statistical accuracy) and the robustness of parallel pre-treatment trends (economic accuracy). Variables that are not part of the final specification, but have been tried without improving the accuracy are, for example, the z-score, the standard deviation of stock returns, or the average bond yield.[20]

Column (1) of Table 4.3.1 shows the results of this regression. It is evident that firms which become eligible for clearing between 2013 and 2017 are different than the average firm in our control sample. Cleared firms have more cash and revenues but are less profitable. Furthermore, they are smaller (measured by total assets) but have higher leverage.

To address concerns of selection into treatment arising from those results, we use a matching approach to select the sample for our analyses. For this purpose, we pair firms using the predicted propensity score of becoming eligible for CC from Equation 4.3. This allows us to only compare firms which were ex-ante similar in their balance sheet characteristics and likelihood of being made eligible for clearing. Table 4.3.2 shows descriptive statistics for the unmatched and the matched sample.[21] The table highlights

[20] The most natural predictor is information from the DTCC about the outstanding volume and trading activity of CDS contracts. The DTCC discloses this information for the 1000 most traded contracts on its website. Unfortunately, these 1000 contracts are global (including contracts from outside the US) and contain sovereign CDS. That is, for many of our control firms we do not observe the relevant factors. We therefore cannot use this information for the propensity score matching. We do observe, however, that for the treated firms where the information is available, there is a high correlation with the other predictors used in our propensity score model.

[21] Table 4.B.3 shows descriptive statistics for all used variables during the estimation sample period.

Table 4.3.1: Eligibility prediction regression

The table presents the results of logit regressions for clearing eligibility. The eligibility dummy takes the value of one for firms that become eligible for clearing between 2013 and 2017, and zero for firms that do not become eligible before 2018 (or at all). Explanatory variables are averages over the eight quarters from 2011Q1 and 2012Q4 in column (1). Explanatory variables are averages over the eight quarters from 2009Q1 and 2010Q4 in column (2). Explanatory variables are values from the quarter directly before the eligibility decision in column (3). N refers to the number of firms in the regression. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Benchmark matching	(2) Matching from 2011	(3) Pre-quarter matching
Cash	0.624***	0.585***	0.213**
	(0.218)	(0.165)	(0.089)
Capex	0.353	-0.058	-0.066
	(0.257)	(0.149)	(0.096)
Revenues	0.589**	0.407*	0.340*
	(0.268)	(0.239)	(0.181)
ROA	-59.52***	-30.29***	-15.54***
	(18.04)	(11.32)	(3.382)
Leverage	3.922*	5.267**	1.084
	(2.333)	(2.287)	(1.645)
Total Assets	-1.851**	-0.460	-1.157
	(0.831)	(0.621)	(0.748)
Total Debt	0.780	0.301	0.966
	(0.668)	(0.578)	(0.737)
N	195	250	210

statistically significant differences of leverage, debt and profitability between treated and control firms in the unmatched sample using bivariate t-tests. After matching, as Panel B demonstrates, there are almost no statistically significant differences between those (or other) variables anymore. Only the differences in leverage remain significant for which we will control in all our regressions.

Table 4.3.2: Descriptive statistics – full vs. matched

The table presents descriptive statistics for the full sample (Panel A) and the matched sample (Panel B). The columns contain the means of the respective variables calculated from 2011Q1 to 2012Q4 both for treated and control firms, the difference between treated and control firms in absolute values, and the p-value of a t-test for equality of the means with unequal variances.

Variable	Mean treated firms	Mean control firms	Absolute difference	P-value t-test
		Panel A – full sample		
Cash	6.6088	6.2816	0.3272	0.23
Capex	5.5466	5.2552	0.2914	0.29
Revenues	7.7211	7.4724	0.2487	0.18
ROA	0.0068	0.0138	0.0070	0.00
Leverage	0.4208	0.2698	0.1510	0.00
Total Assets	9.4099	9.2539	0.1560	0.45
Total Debt	8.4003	7.7633	0.6370	0.00
		Panel B – matched sample		
Cash	6.6088	6.3489	0.2599	0.40
Capex	5.5466	5.326	0.2206	0.48
Revenues	7.7211	7.6242	0.0969	0.63
ROA	0.0068	0.0103	0.0035	0.17
Leverage	0.4208	0.3557	0.0651	0.09
Total Assets	9.4099	9.2538	0.1561	0.50
Total Debt	8.4003	8.1102	0.2901	0.23

Aside from assuring that there is no selection into treatment by firms they must also exhibit a common trend pre-treatment for our results to have a causal interpretation. We examine this assumption for our setting of staggered treatment in Figure 4.3.1. We plot the difference between the treated and control group of two main variables of interest, respectively predictors of eligibility – total assets and total debt. One can see that there are no significant differences in the 10 quarters pre-treatment plotted in the graphs.[22] Significant differences only arise after the eligibility. We have produced corresponding

[22] A joint F-test strongly rejects statistical significance of the sum of those coefficients.

graphs for all variables of our prediction model above, and do not identify any significant pre-treatment deviations. In Section 4.6.3, we further show event study graphs built on regression frameworks with control variables which corroborate that there are no significant differences between treated and control firms before treatment.

Figure 4.3.1: Total debt and total assets – parallel trends

a) Total debt **b)** Total assets

These figures show differences in the mean of total debt (Panel a) and total assets (Panel b) between control firms and treated firms. The dark red are is the 10/90% confidence interval, the light red area is the 5/95% confidence interval.

Taken together, the firms that we use for estimation purposes are statistically non-distinguishable in their relevant balance sheet characteristics pre-treatment. As we are going to show, statistically significant differences in their balance sheet composition will arise after treatment which we will thus interpret causally as treatment effects.[23] Our final matched sample consists of 50 treated and 50 control firms.

A final concern is that our estimates are confounded by the mandatory clearing mandate for index CDS products. This mandate was introduced by the Commodity Futures

[23]All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters (see Tables 4.G.6 to 4.G.8).

Trading Commission in the beginning of 2013.[24] It seems plausible that mandatory central clearing for CDS indices containing almost all our treated firms already had an impact before the single-name contract of the firm gets eligible. Our estimated coefficients would therefore be a lower bound for the true effect of clearing CDS contracts.

If central clearing constitutes a meaningful structural change for firms and this change is not anticipated, markets should react to the announcement of firms being made eligible for clearing by adjusting asset prices. To measure whether this is the case, we set up a standard announcement effect event study. That is, we normalize the time axis for all affected firms around their individual announcement date and track how the stock prices and CDS spreads develop in a short time window before and after the event. We argue that the timing of clearing eligibility is surprising for most market participants because announcements are made very briefly (i.e. a few days) before the implementation date.[25] We choose a window of 5 trading days before and 15 trading days after the event, to capture four trading weeks in total. Prices are adjusted using the Capital Asset Pricing Model (CAPM), by filtering out co-movement of the firm-level prices with the corresponding market index (CDX, respectively SP 500) during the event window. We then run a daily regression of the form:

$$y_{i,t} = \sum_{j=-5}^{15} \theta_j \mathbf{1}(t + j = Eligibility_i) + \alpha_i + u_{i,t}, \tag{4.4}$$

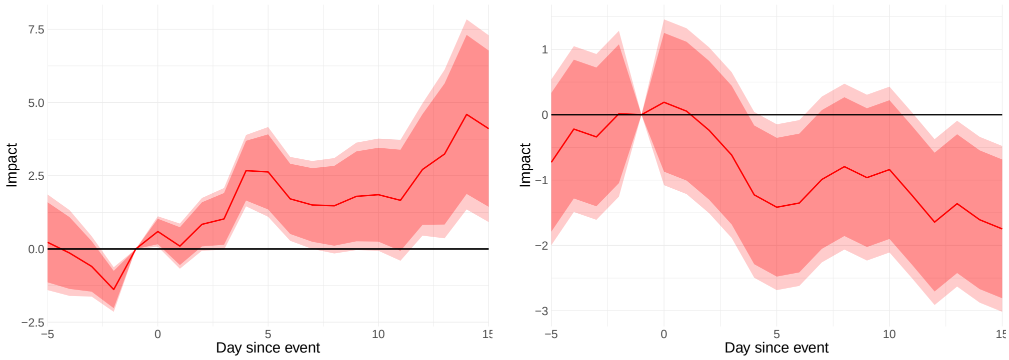
where $\mathbf{1}(t + j = Eligibility_i)$ is an indicator which equals one if firm i becomes eligible for clearing in period $t + j$. The set $\{\theta_j\}_{-15}^{5}$ contains the impact coefficients of clearing eligibility from 5 quarters before until 15 quarters after the date of clearing eligibility. We normalize $\theta_{t-1} = 0$. We add firm fixed effects to control for firm-specific sensitivities of asset prices and other time-invariant firm-level characteristics.

In Figure 4.3.2a we plot the results for CDS spreads. In the two to three days leading up to the announcement there is a small statistically significant downtick potentially hinting at some information leakage. However, this small decrease of approximately 0.5% is eclipsed by an increase in the CDS spreads of 2.5% in the first five days after the

[24] For details see `https://www.cftc.gov/PressRoom/PressReleases/6429-12`.

[25] See `https://www.theice.com/publicdocs/clear_credit/circulars/Circular_2019_047.pdf` for an example of such an announcement. The time between announcement and clearing eligibility is just 3 days.

Figure 4.3.2: Equity prices and CDS spreads around announcement day



a) CDS spreads **b)** Equity prices

The figures show the impact of the announcement of clearing eligibility. The estimation is based on a matched sample of 50 treated and 50 control firms. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is five days pre-announcement until fifteen days post-announcement.

announcement. While this effect first seems to weaken a bit over time (days 7 - 11), it stays statistically significant and of the same magnitude even 15 days after eligibility. Thus, the announcement of clearing eligibility drives up CDS spreads of affected firms. We will elaborate more on the reasons for this upward price pressure in Section 4.4, but since the announcement directly concerns CDS markets, a market reaction is not surprising.[26]

Therefore, we also investigate the stock market reaction to the same announcement. If clearing eligibility is a CDS market phenomenon only, with no implications for firms and their performance, the stock market should not react in any meaningful way to the announcement. In Figure 4.3.2b we plot the corresponding event study for equity prices. There is no statistically significant pre-announcement trend, and if anything, prices were on an upward trajectory. After the announcement, prices sharply drop, however, such that on the third day after announcement the equity value of affected firms already decreased by 1.5% relative to ineligible firms. Just as with the CDS results, this effects weakens temporarily (days 7 and 11), to then pick up speed again and leave equity prices at almost 2% below their pre-announcement value after 15 trading days.

[26]This result is also consistent with Loon and Zhong [2014] who find an increase in CDS spreads after CC eligibility.

Thus, stock markets clearly perceive clearing eligibility as an adverse economic event for affected firms. Most importantly, the results for both asset markets show that the eligibility decision were not anticipated. That is, the data supports the quasi-exogeneity of the treatment assignment in our matched sample.

4.4 A model of Credit Default Swaps and corporate debt

In this section, we present a model environment of the corporate bond and CDS market. The model allows us to capture the main features of CC and to postulate channels through which the CDS market environment can affect demand for firm debt.

We first adapt the basic model presented in Oehmke and Zawadowski [2015] to include counterparty default risk for investors trading CDS contracts. That is, the counterparty of the derivative trade, i.e. the protection seller, might not fulfil its payment obligations. We then introduce CC in a reduced form by assuming that centrally cleared markets have a lower probability of a seller's default. We present closed form solutions for this model that allow us to make predictions about the effects of central clearing on prices of CDS and bonds. Moreover, we introduce non-zero trading costs for CDS contracts. We assume that tradings costs rise when central clearing is introduced, due to higher collateral demand, default fund contributions or trading fees. Our results are general, though, and we do not restrict the trading cost dynamics in any way. We provide a numerical solution for this model, further extending our set of predictions to the CDS trading volume. We thus obtain a full set of hypotheses about the effects of central clearing on the CDS and the bond market in terms of prices and quantities. Lastly, we relate these findings back to firm outcomes such as debt and assets.

4.4.1 Basic model – setup

We start from the model presented in Oehmke and Zawadowski [2015]. There is a financial market with two types of assets, a risky corporate bond and a CDS contract. Bonds are in positive net supply $S > 0$[27] while CDS contracts are in zero net supply. Bonds can be purchased at equilibrium price p. At maturity, the bond repays its face value of 1 with probability $1 - \pi$ and zero otherwise, i.e. the firm that issues the bond defaults

[27] The assumption of a static supply is loosened below.

with probability π. Maturity occurs randomly with Poisson arrival rate λ. Trading the bond incurs trading costs c_b. In particular, the ask price of the bond (i.e. the price when buying the bond) is $p + \frac{c_b}{2}$, while the bid price (i.e. the price when selling the bond) is $p - \frac{c_b}{2}$. Hence, c_b can be interpreted as the bid-ask-spread while p is the midquote price.

Aside from the bond, investors can buy or sell CDS contracts which reference the firm issuing bonds. The CDS contract insures against the default of the firm. It matures jointly with the bond, i.e. at Poisson rate λ. The contract is traded at equilibrium price q. It pays out 1 if the firm defaults and zero otherwise. The CDS contract incurs costs c_{CDS} which we interpret as the costs associated with trading such as posting collateral.[28] We extend the basic model and assume that investors on the CDS markets default on their payment obligations with probability $d > 0$ (which is independent of the firm's default event). In case of a default by the CDS seller, the contract pays out zero regardless of the firm's performance. Similarly, as a CDS seller, one does not have to pay out the insurance amount if the buyer defaults.
Following Oehmke and Zawadowski [2015] our main assumption is

$$c_b \geq c_{CDS} \geq 0.$$

i.e. bonds have higher trading costs than CDS contracts. This is consistent with evidence that CDS markets are more active and that dealer inventory management is more expensive for bonds relative to CDS [see Oehmke and Zawadowski, 2015, for a more detailed discussion]. For most of our analysis we further assume that $c_{CDS} = 0$ which allows us to derive closed form solutions. In the last part of our analysis, we ease this assumption.
Assets are traded by a continuum of risk-neutral, competitive investors with discount factor 1. To generate trading motives in the model, investors vary along two dimensions. First, investor i believes that the bond defaults with probability $\pi_i \in \left[\overline{\pi} - \frac{\Delta}{2}, \overline{\pi} + \frac{\Delta}{2}\right]$. Variation in beliefs about the default probability generates a motive for trade. More optimistic investors take a long position w.r.t. the firm whereas more pessimistic investors take a short position. Additionally, investors have different liquidity needs. In particular, investor i receives a liquidity shock with Poisson intensity $\mu_i \in [0, \infty)$. The arrival of this shock forces an investor to liquidate her position. The investor then exits and is replaced by a new investor with the same beliefs and liquidity needs (to keep the

[28] Since CDS are much more liquid than bonds, we will not interpret the c_{CDS} as the bid-ask spread even though a small part of the costs might be bid-ask spread driven.

model stationary). For investors with stronger liquidity needs (high μ_i) trading costs play a larger role such that they prefer trading CDS rather than bonds. This is because they stand a higher chance of liquidating their position early such that they would incur trading costs twice.

Investors are uniformly distributed across beliefs about the default probability. There is a mass one of investors at each $\mu_i \in [0, \infty)$ such that the conditional density function is given by $f(\pi|\mu) = \frac{1}{\Delta}$. Lastly, to prevent investors from taking infinitely large positions (due to risk neutrality), investors are allowed to only hold one unit of risky assets (i.e. buy one bond, sell one bond, buy one CDS or sell one CDS). Alternatively, investors can buy a hedged position (buy one bond and one CDS, or sell one bond and one CDS). As an outside option, investors can buy a risk-free asset – cash – with zero return.

4.4.2 Basic model – solution

To solve the model we need to derive the value of each asset for all types of investors. The value of buying a bond is given by

$$V_{buyBond,i} = -\Big(p + \frac{c_b}{2}\Big) + \frac{\mu_i}{\lambda + \mu_i}\Big(p - \frac{c_b}{2}\Big) + \frac{\lambda}{\lambda + \mu_i}(1 - \pi_i).$$

Investor i purchase the bond at ask price $p + \frac{c_b}{2}$. With probability $\frac{\mu_i}{\lambda+\mu_i}$, arising from the Poisson processes governing bond maturity and liquidity shock arrival, investors incur a liquidity shock before the bond matures. In that case the investor sells the bond at bid price $p - \frac{c_b}{2}$. With probability $\frac{\lambda}{\lambda+\mu_i}$ the bond matures before a liquidity shock occurs. Investor i believes that the bond defaults with probability π_i. The value of short selling a bond is given by

$$V_{sellBond,i} = \Big(p - \frac{c_b}{2}\Big) - \frac{\mu_i}{\lambda + \mu_i}\Big(p + \frac{c_b}{2}\Big) - \frac{\lambda}{\lambda + \mu_i}(1 - \pi_i),$$

where the interpretation is symmetric to before. In a similar spirit, the value of buying a CDS contract is given by

$$V_{buyCDS,i} = -\Big(q + \frac{c_{CDS}}{2}\Big) + \frac{\mu_i}{\lambda + \mu_i}\Big(q - \frac{c_{CDS}}{2}\Big) + \frac{\lambda}{\lambda + \mu_i}(1 - d)\pi_i.$$

Initially, the contract is bought at price $q + \frac{c_{CDS}}{2}$ and liquidated early with probability $\frac{\mu_i}{\lambda+\mu_i}$ at price $q - \frac{c_{CDS}}{2}$. If the bond matures before any liquidity shock (with probability

$\frac{\lambda}{\lambda+\mu_i}$) the contract pays out the face value if the firm defaults (with probability π_i) and the CDS seller does not default (with probability $1-d$). The value of selling a CDS contract is then

$$V_{sellCDS,i} = \Big(q - \frac{c_{CDS}}{2}\Big) - \frac{\mu_i}{\lambda+\mu_i}\Big(q + \frac{c_{CDS}}{2}\Big) - \frac{\lambda}{\lambda+\mu_i}(1-d)\pi_i,$$

where the interpretation is symmetric to before.

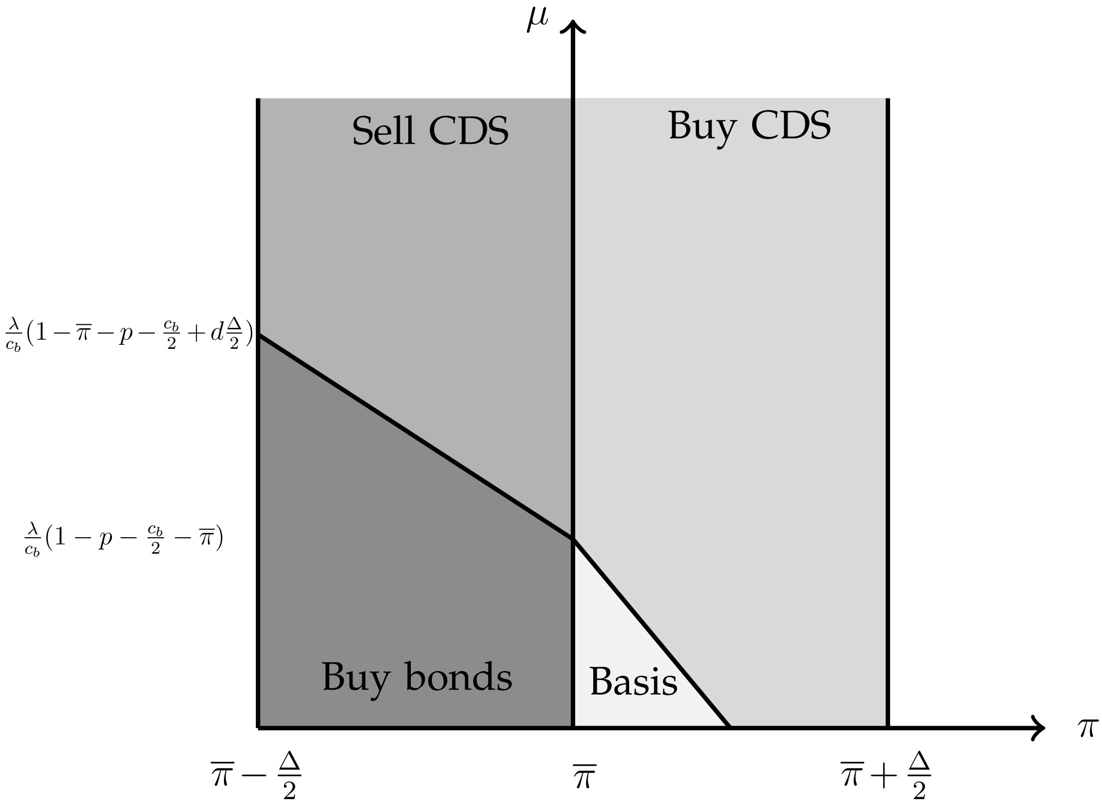
To solve for equilibrium prices we need to determine what type of investors choose which asset (combination). We first determine what type of investor is indifferent between buying the CDS and the risk-free asset. Solving $V_{buyCDS,i} = 0$ with $c_{CDS} = 0$ yields $q_i = \pi_i(1-d)$. At price q_i investor i is indifferent between buying the CDS and the risk-free asset. All investors j with $\pi_j > \pi_i$ get a positive value from buying the CDS. Similarly, all investors j with $\pi_j < \pi_i$ prefer to sell the CDS contract at price q_i. Following Oehmke and Zawadowski [2015], due to the infinite support of μ_i we can employ a limit argument to show that the CDS market clears at price $q = (1-d)\overline{\pi}$ where all investors with $\pi_i > \overline{\pi}$ ($\pi_i < \overline{\pi}$) buy (sell) the CDS contract respectively. Hence, the CDS market is infinitely large and the relative size of the bond market vanishes. This feature allows us to clear markets sequentially, rather than simultaneously.

Given the equilibrium CDS price of q we can then determine bond demand. The optimal decision of all agents is shown in Figure 4.4.1. The x-axis shows the range of believes regarding the bond's probability of default while on the y-axis shows the size of the μ_i which governs the probability of a liquidity shock. Relatively optimistic investors (with low π_i) and smaller probability of liquidity shocks (low μ_i) prefer to buy bonds over all alternatives as shown in the dark grey trapezoid. In addition, there is a set of more pessimistic investors, that still buy the bond but also buy a CDS to hedge their portfolio (light grey triangle). Total bond demand is given by the area of the trapezoid plus the area of the triangle multiplied by the conditional density function $f(\pi|\mu) = \frac{1}{\Delta}$. Setting demand equal bond supply S gives:

$$\frac{1}{\Delta}\Bigg(\bigg(\frac{\lambda}{c_b}\Big(1-\overline{\pi}-p-\frac{c_b}{2}+d\frac{\Delta}{2}\Big)+\frac{\lambda}{c_b}\Big(1-p-\frac{c_b}{2}-\overline{\pi})\Big)\bigg)\frac{\Delta}{2}+\frac{1}{2}\frac{\lambda}{c_b}\Big(1-\overline{\pi}--p\frac{c_b}{2}\Big)^2\Bigg) = S$$

Solving for p yields the equilibrium bond price.

Figure 4.4.1: Bond and CDS trading



Proposition 1. *With $c_{CDS} = 0$, the equilibrium CDS price is $q^* = (1-d)\overline{\pi}$ and the equilibrium bond price is*

$$p^* = 1 - \overline{\pi} - \frac{c_b}{2} + \frac{\Delta}{2} - \sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}$$

Proof: *See Appendix 4.D.*

Note that setting $d = 0$ yields the same equilibrium bond price as in Oehmke and Zawadowski [2015]. With this model we want to study the effect of CC on bond and CDS prices. As argued, e.g. by Loon and Zhong [2014], CC lowers the counterparty risk. Hence, we want to know how prices change when d decreases. Proposition 2 shows the results.

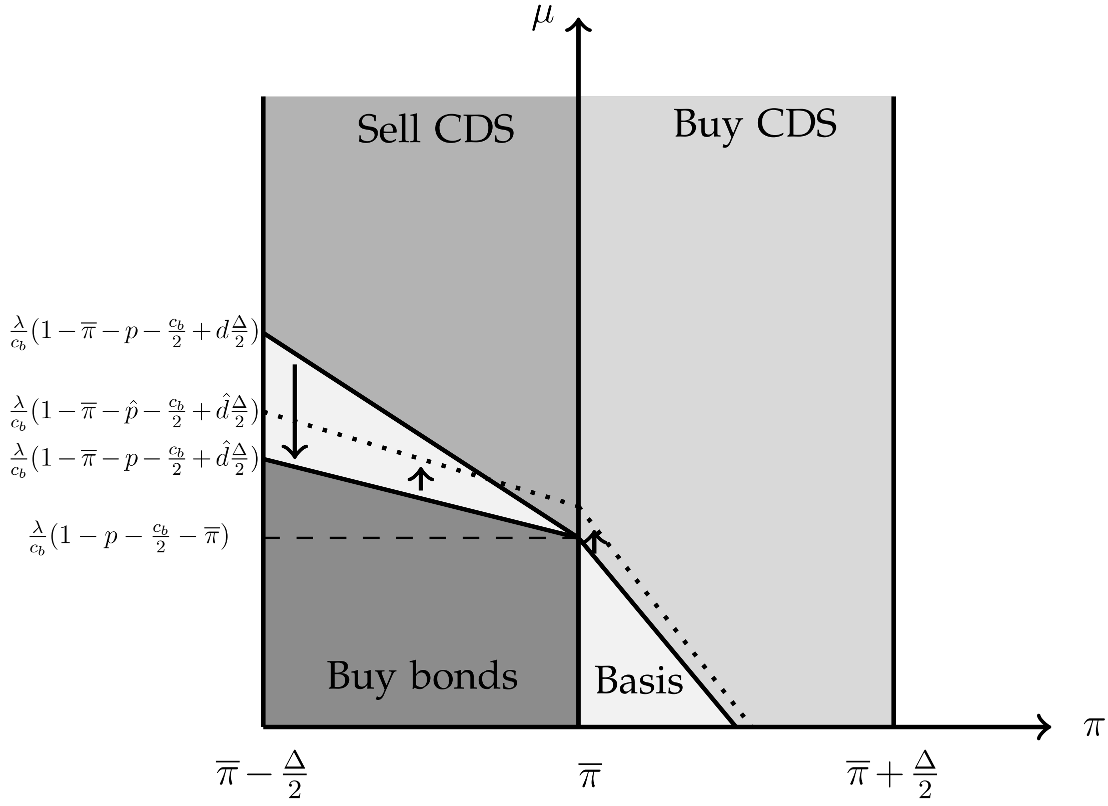
Proposition 2. *A lower counterparty default probability d increases the CDS price q^* and lowers the bond price p^*.*
Proof:

$$\begin{aligned} \frac{\partial q^*}{\partial d} &= -\overline{\pi} < 0 \\ \frac{\partial p^*}{\partial d} &= \frac{\Delta^2}{8\sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}} > 0 \quad \square \end{aligned}$$

q^* increases when d decreases. The lower counterparty default probability increases the expected payout of the CDS when the firm defaults, mechanically raising the price for this insurance. A lower d therefore shifts the upper side of the "Buy bond" trapezoid downwards by increasing the set of investors willing to sell CDS contracts. This is illustrated in Figure 4.4.2. We label the shift of investors from buying bonds to selling CDS contracts as the "arbitrage channel". The arbitrage channel puts downward pressure on the bond price given the fixed supply S. This incentivizes more investors to enter a hedged position of jointly buying the bond and the CDS contract instead of only buying CDS contracts, as can be seen from the outward shift of the "basis" triangle. This mitigates the bond price impact of the "arbitrage channel" effect without ever fully compensating for it.

In this section we discussed an equilibrium with fixed bond supply. In the empirical setting, bond supply is not fixed, however. Including bond supply as a function of bond prices allows us to talk about both price and quantity effects. Assuming that the supply

Figure 4.4.2: Bond and CDS trading – decrease in d



function is upward sloping (the firm wants to issue more debt with higher bond prices), we can show that there will always be a split of the adjustment between the price and the supply, the relative size of which depends on the functional form of bond supply. We document this in Appendix 4.C, where we also provide closed form solutions for the special case where bond supply is a linear function.

4.4.3 Costly trading of CDS contracts

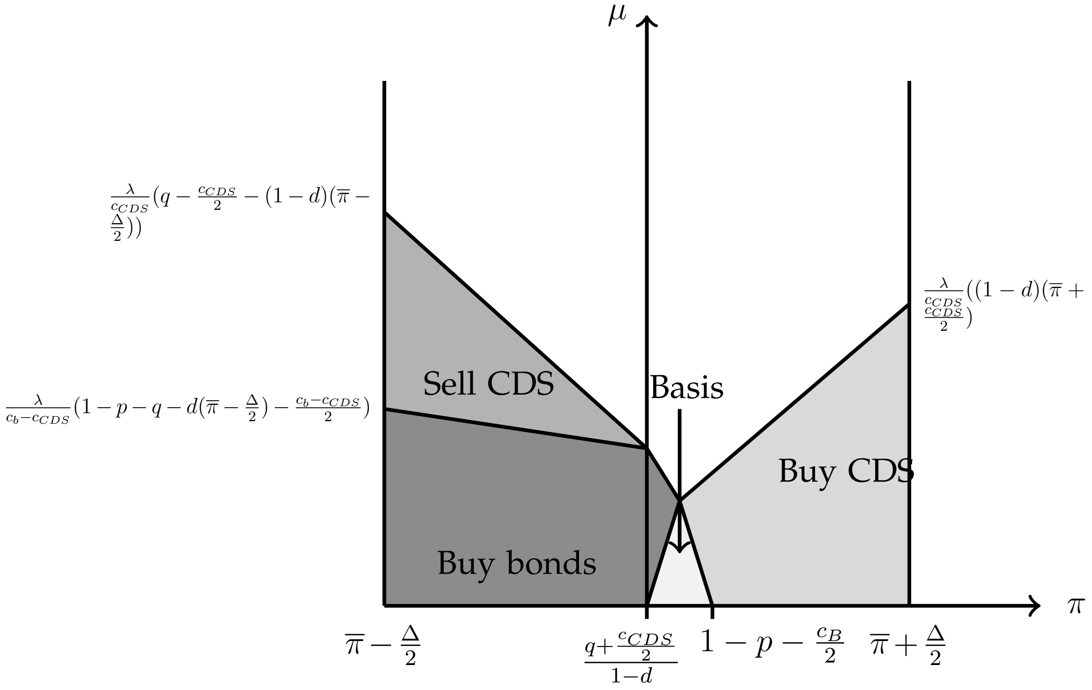
The reduction in counterparty default risk stimulated through the central clearing reform does not come for free. While the market restructuring helps in achieving this goal, there are costs for traders associated with it: higher collateral requirements (initial and variation margins), contributions to CCP default funds and fees to access the CCP. To capture this, we allow for $c_{CDS} > 0$ in this section. This enables us to consider the comparative static of the model solution with respect to d (as before) and c_{CDS}.

In terms of modelling, introducing $c_{CDS} > 0$ implies that we can no longer solve the model in closed form but have to rely on numerical solutions. The reason for this is that the CDS market is not infinitely large anymore, hindering us from solving for market clearing on the CDS and the bond market sequentially. On the upside, this allows us to explicitly measure the impact of central clearing not only on CDS pricing (as before) but also on the volume of CDS traded.

For the purpose of solving the model, we have to define two market clearing conditions, both dependent on p and q, which we solve jointly. The regions defining the supply and demand of bonds and CDS that are used as the inputs for the market clearing conditions can be seen in Figure 4.4.3. It becomes apparent that the regions of selling and buying CDS are no longer unbounded at the top. Since there are costs of trading CDS contracts now, investors facing a risk of liquidity shocks which is too high, no longer want to trade anything else but the risk-free asset. The market clearing condition for the CDS market therefore implies equating the ″Sell CDS″ triangle (supply) and the sum of the ″Buy CDS″ triangle and the ″basis″ triangle (demand). Similarly, the market clearing condition for the bond market implies equating the ″Buy bond″ trapezoid and triangle and the ″basis″ triangle (demand) with the supply S. We then jointly solve these two equations for the two market prices $\tilde{p}$ and $\tilde{q}$.

Even without an analytical solution, the effects of a decrease in d and increase in c_{CDS} can be easily observed in Figure 4.4.3. As before, a decrease in d leads to an increase in the attractiveness of the CDS market thereby increasing the equilibrium price and now also the trading volume. As this implies that some investors switch from buying bonds to selling CDS contracts (the arbitrage channel), the bond price and demand shrink. This induces more investors to conduct the hedged trade. An increase in c_{CDS} has the opposite effects as it makes the CDS market less attractive. An equal amount of investors leaves the CDS market on the buying and selling side by switching to the risk-free asset. However, there is an additional set of investors switching from selling CDS to buying bonds thereby creating an excess demand for CDS contracts. Thus, the equilibrium price of CDS contracts has to rise to achieve market clearing. Compared to a decrease in d, an increase in c_{CDS} therefore also increases the equilibrium price of the CDS market, but lowers the CDS trading volume. As some investors switch from

Figure 4.4.3: Bond and CDS trading - $c_{CDS} > 0$



selling CDS contracts to buying bonds, the bond price and demand rise. This induces fewer investors to conduct the hedged trade (hedging channel).

In summary, a simultaneous decrease of d and increase of c_{CDS} which characterizes the introduction of central clearing has one unambiguous effect: an increase in the CDS price $\hat{q}^*$. The effects on bond prices, and trading volumes of both CDS contracts and bonds depend on the relative size of the arbitrage and hedging channel.[29]
Section 4.5.1 empirically investigates the outcomes for quantities and prices on the bond and CDS market to disentangle the two channels. Taking these results as given, we can then ask if the model can qualitatively generate these outcomes and infer how large the two changes, and the associated channels, need to be in relation to each other to be consistent with the observed empirical results. To tackle this question, we calibrate the model in Section 4.F to moments from our data set.

[29]For a better illustration of the argument above we refer the reader to Appendix 4.E where we discuss the comparative statics of this model in a numerical example. Which channel dominates, depends, in the end, on the set of parameter values and assumed changes in d and c_{CDS}.

4.5 Channel of Effect - Hedging or Arbitrage?

In this section we investigate the presence and relative strength of the two channels through which derivative market reforms could propagate to firms' capital structure postulated in Section 4.4: the hedging channel and the arbitrage channel.

4.5.1 Testing model predictions in firm-level data

Regardless of the relative size of the two channels, our model predicts that central clearing will positively affect CDS prices. To investigate this in our sample, we use the CDS spread as a LHS variable in estimating the staggered diff-in-diff specification in Equation 4.1 where we additionally employ the z-score as a control for the firm's default risk.[30] The result can be found in column (1) of Table 4.5.1.[31] The point estimate indicates a statistically significant increase in the CDS spread of around 20 basis points on average, as expected.

To analyze whether the price increase in the CDS spread is accompanied by a drop in demand for the firms' debt, we estimate Equation 4.1 using total outstanding bond debt, bond issuance and bond yields as the dependent variables. The requirements for bonds to be included are that they have a maturity of more than one year, are senior debt and dollar-denominated. We control for lagged values of the bond rating, its liquidity as measured by the bid-ask-spread and its return. Column (2) documents that the volume of outstanding bond debt, the quantity on the bond market, decreases by 2.2%. Column (3) shows that the issuance of bonds relative to total assets of affected firms significantly decreases by two percentage points, on average.[32] That is, quantity decreases strongly, driven by a reduction in bond issuance. If demand remained stable, this would imply by simple intuition and by the equilibrium outcome of our model in Section 4.4 that the bond yield (price) goes down (up). However, column (4) of Table 4.5.1 shows that bond yields of eligible firms increased by 30 bps, on average, even though this coefficient is not statistically significant. That is, even though supply declines, interest rates with-

[30] The CDS spread is directly linked to the default probability of the firm for which the z-score is a proxy (cf. Hull et al. [2004]). Hence, we will use the z-score as a control variable in all regressions related to the CDS market. Those are columns (1), (4), and (5) in Table 4.5.1.

[31] All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters as well as data before 2011 (see Tables 4.G.3 and 4.G.7).

[32] The decrease in bond issuance without scaling by assets is almost 18%.

Table 4.5.1: Market impact of clearing eligibility

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) CDS spread	(2) Outstanding bond debt	(3) Bond issuance	(4) Bond yield	(5) CDS notional
$Eligibility_i$	19.54**	-0.022**	-0.020*	0.300	0.033
	(7.95)	(0.009)	(0.010)	(0.291)	(0.042)
Matched sample	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	1813	2363	2000	2455	1696
adj. R^2 (within)	0.79	0.93	0.23	0.43	0.29

stand the downward pressure, consistent with a pronounced decline in the demand for bonds clearing the market. This is in line with the arbitrage channel. Investors switch from buying corporate bonds of eligible firms to selling CDS contracts for which one can now obtain a higher price (cf. column (1)).

In column (5) of Table 4.5.1, the LHS variable is the natural logarithm of outstanding CDS notional. The estimate is not statistically significant, while the point estimate is positive with 3.3% higher outstanding notional. Together with the higher price for CDS products observed in column (1), a stable quantity on this market implies that the demand for CDS products has gone up. The empirical findings are therefore consistent with the arbitrage channel, which thus dominates the hedging channel. We investigate the relative strength of the two channels in more detail in the model calibration in Section 4.F. We find the arbitrage channel to be several times as important as the hedging channel.

4.5.2 Testing model predictions in security-level data

To corroborate the evidence found at the firm-level, we further analyze the security-level holdings of US mutual funds. We use data from the WRDS Mutual Fund Holdings database and identify bonds issued by and CDS contracts written on the firms in our matched sample.[33] Using a specification similar to Equation 4.1, we examine how holdings of these securities have changed due to clearing eligibility:

$$y_{i,f,t} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_{f,t} + u_{i,b,t} \tag{4.5}$$

with firm FEs (α_i), controls ($\mathbf{x_{i,t-1}}$), and fund $\times$ quarter FEs controlling for the overall demand of mutual funds for bonds/CDS of all firms. The dependent variable $y_{i,f,t}$ is the sum of all holdings by mutual fund f at time t of bonds issued by (CDS written on) firm i, measured as a share of total net assets of the fund.

The results can be found in Table 4.5.2. Column (1) shows that mutual funds reduce their holdings of eligible bonds compared to non-eligible bonds significantly. The economic magnitude of the effect is large with a coefficient estimate that is roughly half as large as the average firm-specific bond exposure of mutual funds. This direction of effect mirrors the firm-level results. The results for CDS contracts in column (2) document that the net exposure with respect to the CDS contracts of eligible firms has been reduced compared to non-eligible firms. The size of the effect is roughly one third of the average firm-specific CDS exposure. This reduction in the net exposure can either be due to an increase of the short position (what the arbitrage channel postulates) or due to a decrease of the long position (what the hedging channel postulates). To differentiate between the two, we re-run the analysis in column (3) looking at short positions only. The coefficient shrinks in size and significance but stays in the statistically significant region. This suggests that the reduction in CDS exposure is driven by an increase in short positions. It is also important to note that we can clearly rule out an increase in the overall net CDS exposure. If the CCP somehow chose firms which were on worse trajectories pre-clearing, the reduction in bond demand by mutual funds should be accompanied by an increase in net CDS holdings. This is not what we observe. The concurrency

[33] Bonds can be identified using cusips. For CDS contracts we combine security name string matching with manual inspection, comparable to Jiang et al. [2021].

of lower bond holdings and higher CDS short positions strongly suggest the arbitrage channel to be an important driver of the economic dynamics.

Table 4.5.2: Mutual fund holdings impact of clearing eligibility

The table presents results of running regression specification 4.5. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are z-score, average bond rating, bond bid-ask spread, bond return and CDS spread. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Bond volume	(2) CDS volume	(3) CDS volume (short)
$Eligibility_i$	-0.0006*	-0.0004**	-0.0002*
	(0.004)	(0.0002)	(0.0001)
Matched sample	Yes	Yes	Yes
Fund $\times$ Time FEs	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	3489081	262434	262038
adj. R^2 (within)	0.048	0.005	0.008

4.6 Real effects

If firms lose bond financing are they trying to compensate for this loss by other types of debt, in particular bank loans? And are there aggregate effects on the balance sheet and the performance of affected firms? This section answers these questions sequentially.

4.6.1 Credit demand

Did firms try to compensate for the loss of bond funding by demanding more bank loans? To answer this question, we examine the syndicated loan market which is by far the most important source of bank financing for large firms in the US. For this purpose, we retrieve data from Refinitiv Dealscan and hand-match the borrowers to our matched sample. We allocate 100% of the loan to the lead arranger following other papers in the

literature, e.g. Ivashina [2009].
We proceed in two steps. First, we estimate a specification similar to Equation 4.1:

$$Loan_{i,b,t} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_b + \alpha_t + u_{i,b,t} \tag{4.6}$$

with bank FEs (α_b), firm FEs (α_i), time FEs (α_t) and firm controls ($\mathbf{x_{i,t-1}}$). The dependent variable $Loan_{i,b,t}$ is the amount of loans extended from bank b to firm i at time t. This will help us understand whether cleared firms receive more credit than non-cleared firms, controlling for a host of confounding factors. However, this approach does not tell us whether firms increased demand for bank loans. Instead, it only shows the effect of CC on the equilibrium outcome. To disentangle supply and demand, we run a second set of regressions in the spirit of Khwaja and Mian [2008] of the following form:

$$Loan_{i,b,t} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \alpha_i + \alpha_{b,t} + u_{i,b,t}. \tag{4.7}$$

By including $bank \times time$ FEs we can control for the credit supply provided by bank b at time t. To identify this effect we only include banks that lend to more than one firm in every period. Since this is the case for most banks in our sample we are left with sufficient variation to identify the demand of firms for additional credit, captured by θ. We call this the "inverted" Khwaja and Mian [2008], since we control for supply instead of demand.[34]

The results can be found in Table 4.6.1 which displays the estimates for θ. In columns (1) and (2), we use exposures measured in USD between bank b and firm i as the dependent variable, in columns (3) and (4), we use log exposures, and in columns (5) and (6) we use the exposure scaled by the level of previous quarter assets of the borrower. All measures of credit paint a similar picture. Cleared firms receive more credit than non-cleared firms (columns (1), (3), and (5)). The coefficient in column (1) states that the loan size from bank b to firm i increases by around \$20 Mio. after the firm becomes eligible for clearing. This effect is statistically significant. Similarly, the log exposure increases by 0.27 points (column(3)) and the exposure in terms of total assets increases by

[34] In Khwaja and Mian [2008] the authors estimate the effect of liquidity shocks on bank lending. For that purpose they need to control for credit demand by firms. By including only loans to firms, which have lending relationships with two or more banks the authors can control for credit demand by including firm×time FEs.

3.3% (column (5)). These effects are statistically significant and are relative to uncleared firms.

In columns (2), (4) and (6), we see that the coefficients are still positive after controlling for bank credit supply. That is, firms have been demanding significantly more credit from banks after becoming eligible for clearing. The demand from firm i for loans from bank b in dollars increases by $27 Mio (column (2)). The log exposure increases by 0.34 points and the exposure in terms of total assets increases by 4%.

Comparing the sizes of the coefficients between the two specifications (the equilibrium outcomes in the first set of regressions and the demand estimates in the second set of regressions), we note that the latter estimates are larger. This suggests that the increase in credit demand was larger than the amount of credit extended to the firms, i.e. firms could not compensate for the loss in bond funding to the extent that they wanted to.

Table 4.6.1: Overall loans

The table presents results of running regression specifications 4.6 and 4.7. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 383 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	20.456***	26.618**	0.274***	0.337***	0.033*	0.040*
	(7.331)	(9.973)	(0.080)	(0.099)	(0.018)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,658	35,658	35,658	35,658	35,658	35,658
adj. R^2 (within)	0.500	0.420	0.486	0.395	0.709	0.666

To better understand the exact reaction of firms, we split the loans into two groups: term loans and credit lines. A term loan is an actual on-balance sheet credit granted to the firm, which typically has a medium-term maturity (one to five years). A credit line is an off-balance sheet credit limit promised to the firm, which can be drawn down in the case of liquidity needs and converted to an on-balance sheet exposure. Credit lines usually have short-term maturities ($\leq$ one year). If firms need to secure additional short-term liquidity to compensate for the loss of funding on debt markets, it is more likely that they increased their demand via credit lines than term loans.

Table 4.6.2: Credit lines

The table presents results of running regression specifications 4.6 and 4.7 with the sample being restricted to loans that classify as credit lines. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 333 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	20.387***	26.569***	0.259***	0.300***	0.029**	0.031**
	(6.211)	(8.355)	(0.071)	(0.084)	(0.012)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,423	30,423	30,423	30,423	30,423	30,423
adj. R^2 (within)	0.528	0.464	0.503	0.420	0.749	0.715

Table 4.6.2 shows the results for credit lines. All coefficients have a similar size as in Table 4.6.1. They are all statistically significant. The overall amount of credit lines increases by \$20 Mio. after becoming eligible for clearing (column (1)). The log exposure increases by 0.26 points (column (3)) and the amount in terms of total assets increases by 2.9% (column (5)). Similar to the previous table, the coefficients estimating the increase in demand are somewhat larger, indicating that their demand is not fully met. Overall demand for credit lines increases by \$27 Mio. (column (2)), by 0.3 points in log terms (column (4)) and by 3.1% in terms of total assets. One caveat in our analysis is that we cannot observe whether credit lines are actually drawn. Nevertheless, our results suggest that, even if credit lines are not used, firms' demand for access to short-term liquidity increases after becoming eligible. This interpretation is in line with our previous results. Firms want to have quick access to cash because they lost funding on the bond market. While all the effects documented in Table 4.6.1 can be reproduced for credit lines, no significant coefficients turn up in the term loan specification in Table 4.6.3. Thus, the demand increase of firms for loans is entirely driven by additional demand for credit lines, i.e. short-term liquidity.

Table 4.6.3: Term loans

The table presents results of running regression specifications 4.6 and 4.7 with the sample being restricted to loans that classify as term loans. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. We identify 173 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	3.516	-12.197	0.025	-0.062	0.017	-0.007
	(4.160)	(9.349)	(0.026)	(0.054)	(0.018)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,235	5,235	5,235	5,235	5,235	5,235
adj. R^2 (within)	0.690	0.434	0.850	0.699	0.760	0.531

4.6.2 Balance sheet effects

Any relevant and persistent change to the economic environment of a firm, and particularly the debt funding situation, is eventually captured on the balance sheet. In particular, the reduction in bond demand and the insufficient bank credit supply suggest effects on major balance sheet items such as total debt, total assets or leverage. Examining these variables should tell us more about the economic relevance and magnitude of central clearing effects.

Table 4.6.4 shows the results from estimating Equation 4.1. Unless otherwise stated, the set of controls include the (lagged) log of total assets, leverage, revenue, cash, capital expenditures, total debt as well as the return on assets. The most direct link between a reform of the CDS market and firms' balance sheet is corporate debt. Hence, column (1) of Table 4.6.4 shows the impact of central clearing eligibility on the total debt levels of firms. The point estimate is highly statistically significant and indicates that firms reduced their debt level by 2.7% as a response to their CDS becoming eligible for clearing. The most liquid CDS contracts have a maturity of five to ten years and many investors want to hedge against corporate bonds which they are holding. Since most corporate bonds also have maturity of more than one year, long-term debt (defined as maturity

> one year) should be more strongly affected by the CDS market reform. Column (2) of Table 4.6.4 confirms this assertion with a highly significant coefficient of -2.9%. The corresponding coefficient for short-term debt is not significant (not tabulated).[35]

If firms lose part of their funding, the natural question is whether this affects their overall firm size (measured as total assets) or whether they are able to compensate for the loss in debt funding. Column (3) of Table 4.6.4 shows that firms in fact shrink by 1.6%, on average. Column (4) then shows that affected firms do significantly reduce their leverage by 0.4 percentage points. That is, they reduce their debt slightly more than assets and adjust their capital structure. Column (5) confirms that firms do not increase equity to compensate the loss in debt funding on the liability side of the balance sheet. The coefficient suggests that equity even decreases by 0.9%. However, the coefficient is imprecisely estimated.[36]

Table 4.6.4: Balance sheet impact of clearing eligibility

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.027***	-0.029***	-0.016**	-0.004*	-0.009
	(0.009)	(0.01)	(0.007)	(0.002)	(0.016)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	3000	3000	3000	3000	2756
adj. R^2 (within)	0.81	0.81	0.88	0.80	0.81

[35] In column (2), total debt is not among the control variables to avoid multi-colinearity issues with long-term debt.

[36] In the appendix, we show an unmatched sample version of Table 4.6.4 in Table 4.G.1. One can see that ignoring the endogeneity in the eligibility selection would bias the results downwards with an even stronger effect on debt.

Summing up, a firm that becomes eligible for clearing loses a significant portion of its (long-term) debt funding which results in a balance sheet size reduction. This tells us that the substitution from bonds to bank loans is less than one-to-one. In the following we want to analyze the dynamics of these effects. Do firms reduce debt and assets immediately or is this a slow but steady process?

4.6.3 Timing of balance sheet effects

To present our event study results we plot the impact coefficients $\{\theta_j\}_{-k}^{l}$ from estimating Equation 4.2. We use the following set of lagged controls: leverage, revenue, cash, and capital expenditures. The impact window starts 4 quarters before the time of clearing eligibility and ends 12 quarters afterwards. The plotted confidence intervals are at the 90- and 95-percent level, respectively. Coefficients are normalized such that $\theta_0 = 0$.

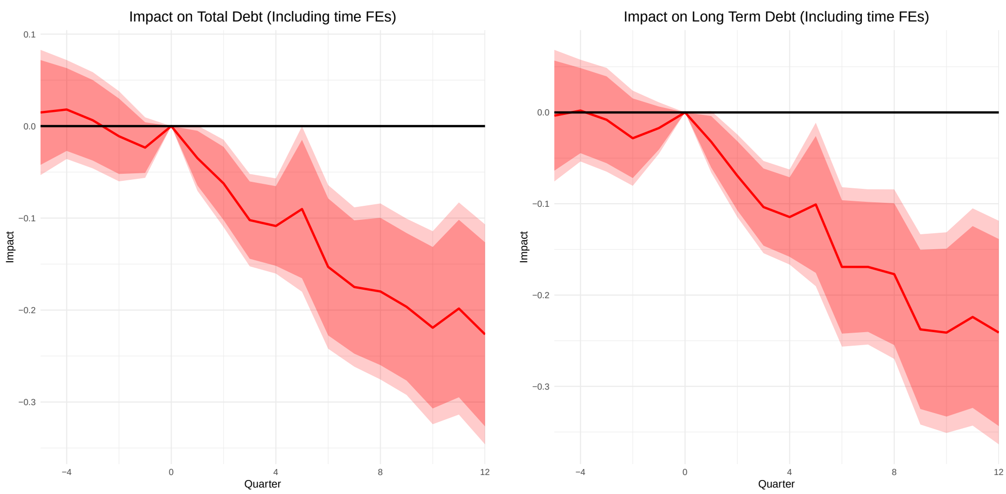
The corresponding results to columns (1) and (2) of Table 4.6.4 are plotted in Figure 4.6.1. We plot the impact of central clearing on total debt (Panel 4.6.1a) and long-term debt (Panel 4.6.1b). First, consider the left panel. Total debt declines very rapidly and persistently. The effect seems to level-off roughly eight quarters after the treatment. Just as in the raw examination in Figure 4.3.1, there is no significant pre-trend in this regression framework which strengthens our conjecture of causal effects. The dynamics are very similar for long-term debt.

The counterparts to columns (3) and (4) from Table 4.6.4 in Figure 4.6.2 are Panel 4.6.2a, displaying the impact on total assets, and Panel 4.6.2b, displaying the impact on leverage. Total assets in the left-hand panel appear to be considerably more sticky than debt. The

first four to five quarters after eligibility total assets barely react significantly. Only in the sixth quarter they start dropping to significantly lower levels representing a substantial shrinkage of those firms. The right hand panel reveals that the reaction of leverage is very imprecisely estimated, but does not suggest that leverage is moving in any direction in the long-term.

We therefore document an immediate and economically sizeable impact of CDS clearing eligibility on underlying firms' debt levels which translates into considerably smaller balance sheet size in the two to three years following the treatment.

Figure 4.6.1: Debt after clearing eligibility



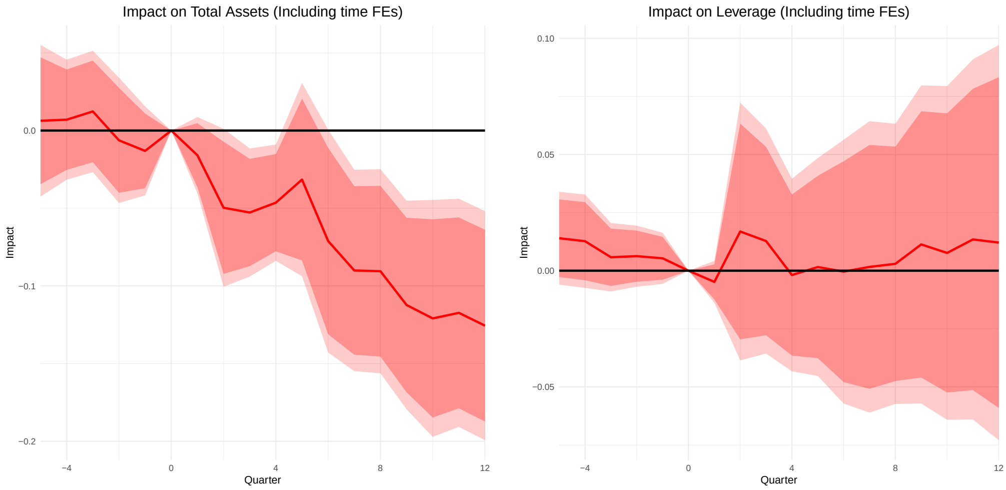
a) Total debt **b)** Long-term debt

These figures show the eligibility impact coefficients and confidence intervals from running regression specification 4.2. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is four quarters pre-treatment until twelve quarters post-treatment.

Why have firms not been able to fully compensate for the loss of market-based funding by bank credit, as indicated by the total debt reduction on their balance sheet? Limits to financial flexibility are likely to be one main driver of the insufficient substitution between debt types (cf. Graham and Harvey [2001]; Denis [2011]; others). As documented in Section 4.3, eligible firms have comparatively high cash levels which are associated with financial frictions, respectively low flexibility in funding choices. One concrete possible explanation is that firms could not increase their bank credit volume further without facing higher, and potentially unfavorable, interest rates. Our data suggests that interest rates for the additional credit lines have not been significantly higher, implying that firms just might have negotiated as much as they could without facing higher borrowing costs.[37]

[37] To obtain this finding, we repeat the regressions of Table 4.6.1 with interest rates as the dependent variables. In untabulated results, we find no significance for the eligibility dummy.

Figure 4.6.2: Assets and leverage after clearing eligibility



a) Total assets **b)** Leverage

These figures show the eligibility impact coefficients and confidence intervals from running regression specification 4.2. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. The dark red area is the 10/90% confidence interval, the light red area is the 5/95% confidence interval. The estimation window is four quarters pre-treatment until twelve quarters post-treatment.

4.6.4 Firm input choices and performance

Based on our theoretical and empirical considerations so far, can we make predictions about firm performance? Consider the firm to have a standard Cobb-Douglas production function with decreasing returns to scale and two inputs. These are capital (financed via debt) with price $1/p - 1$ and labor with wages w. The decrease in bond demand reduces the firms' demand for capital (to equalize marginal returns to capital and its price). In turn, marginal returns to labor also decrease with less capital available, prompting firms to reduce the amount of labor to again equalize marginal returns and costs. Lastly, profits decrease with less production and higher input prices. Hence, a standard model of a firm would additionally predict less investment in capital, less employment and lower profits after firms become eligible for CC. To measure this, we estimate regression models as specified in Equation 4.1:

$$y_{it} = \theta \mathbf{1}(t \geq Eligibility_i) + \beta \mathbf{x}_{i,t-1} + \delta y_{i,t-1} + \alpha_i + \alpha_t + u_t,$$

using the following LHS variables: plants, property and equipment (PPE; as a proxy for capital inputs), employment (as a measure of labor inputs), return on assets (as a measure of profits), and the stock price (as a market-based measure of the firms' performance). We employ the same empirical strategy as before, using the temporal variation in clearing eligibility and the matched sample from Section 4.6.2 to estimate the regression.

Table 4.6.5 displays the results.[38] Column (1) shows that PPE shrinks significantly by 1.5%. To alleviate any worries that cleared firms might be firms who coincidentally face higher depreciation, columns (2) looks at net PPE. The result is roughly the same with an estimate of 1.4%. Hence, eligible firms reduce their capital inputs to production.

Table 4.6.5: Real effects of clearing eligibility

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 50 treated and 50 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Gross PPE	(2) Net PPE	(3) Employment	(4) ROA	(5) Stock price
$Eligibility_i$	-0.015***	-0.014**	-0.036	-0.0023*	-0.033*
	(0.006)	(0.006)	(0.021)	(0.0013)	(0.018)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	2278	3000	552	3000	2913
adj. R^2 (within)	0.87	0.87	0.65	0.00	0.68

Employment in column (3) drops by 3.6%, on average, implying that firms also have to reduce their labor input in line with our theoretical prediction although this estimate is not statistically significant.[39] Are firms less profitable? Column (4) indicates that the return on assets of eligible firms is roughly 0.23 percentage points lower than the

[38] All our results are robust to a matching algorithm using balance sheet variables in the pre-treatment quarters as well as only data before 2011 (see Tables 4.G.4 and 4.G.8).

[39] The regression using the log of the number of employees on the LHS is on annual data because this variable is only available at yearly frequency.

one of non-affected firms, on average. This coefficient is statistically significant. In untabulated results we investigate the cause of the profitability decline. While revenues stay unaffected, net income declines. This suggests that production cost have gone up, and indeed we find costs of goods sold to be significantly higher. The effect on stock prices as a gauge of the outlook of the firm is also statistically significant, with the point estimate suggesting a decrease in stock market valuation of 3.3% for eligible firms.

Summing up, the results suggest that becoming eligible for clearing – implying a loss in debt funding and a reduction of the balance sheet size – is not beneficial for the affected firms. They reduce their capital stock, become less profitable and suffer a decrease in stock market valuation. It is therefore important to stress that CC eligibility of firms does not only affect their capital structure but also their real economic performance.

4.7 Conclusion

In this paper, we show that central clearing of single-name corporate CDS contracts has a sizeable effect on the capital structure of affected firm. After becoming eligible for clearing, firms decrease their debt levels by 2.7%, an effect that is even stronger for long-term debt. As a response, firms shrink their balance sheets by reducing total assets by around 1.6%. The effects we identify are both statistically and economically significant. Importantly, we document empirically that the impact of central clearing on the funding situation of firms has real economic effects as those firms decrease their capital stock, turn less profitable and lose in stock market valuation. To mitigate these effects, firms respond by demanding more bank loans. However, they are not able to fully compensate for the initial loss in funding.

We use a theoretical model for the CDS and corporate debt markets to describe how a change in the CDS market structure can affect demand for firms' debt. We introduce central clearing in this setup by focusing on two features: lower counterparty risk and higher trading costs. We obtain theoretical predictions which allow us to disentangle two channels of effect – the arbitrage and the hedging channel.
We show that the arbitrage channel (lower counterparty risk on the cleared market) appears to be the major part of the explanation. Our theory predicts that, due to lower

risk on the CDS market, investors switch from the bond market to the CDS market driving bond demand down and CDS demand up. We empirically document both of these demand shifts using firm- and security-level data.

These results have important implications. From a policy maker's perspective we demonstrate that there are potential trade-offs between financial stability (through more clearing of derivatives resulting in lower risk) and promoting real economic outcomes. Although derivative markets are, arguably, safer compared to before the GFC this comes at the cost of real economic externalities. Most likely, the implications for non-financial firms go beyond the credit derivative market that we explore in our paper as interest rate, exchange rate or weather derivatives are important financial products for the real economy, too, many of which are subject to clearing policies.

Appendix

4.A Central Clearing Counterparties - Overview and history

This section first describes CCPs in general. Then, we briefly discuss the history of central clearing.

4.A.1 How do CCPs work?

To illustrate the workings of a CCP first consider a traditional, bilateral over-the-counter (OTC) derivative market for CDS where participants directly trade with each other.[40] As an example, *Bank A* wants to insure its credit exposure to *Firm A*. To do so it enters into a trade with *Bank B*. Both parties agree that the former will make regular payments (the coupon, expressed as a spread over some benchmark interest rate) to the latter. In return, *Bank B* agrees to compensate *Bank A* for its losses in case *Firm A* defaults. Additionally, both banks may agree on initial margins and collateral. These two entities are not necessarily the only participants in the market. There may be other financial institutions which trade with each other, e.g. *Bank B* could insure itself against a default of *Firm A* and to earn a profit on the difference in coupon payments without taking on risk.

The result is a network of financial exposures with financial institutions as nodes. In such a network, every player is possibly exposed (on a gross basis) to everyone else. As long as financial conditions remain calm, this market structure works perfectly fine. However, once banks start to default, problems which initially affect a small number of institutions can spread through the entire network, leading to contagion. Coming back

[40]For a more detailed overview see Duffie et al. [2010]; Domanski et al. [2015].

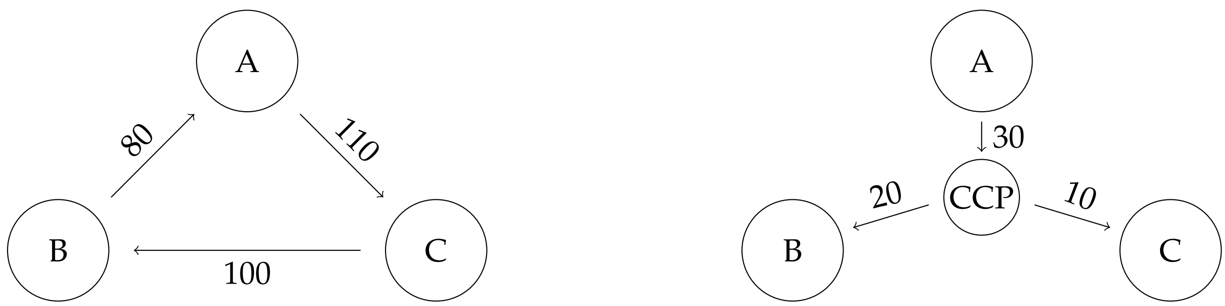
to the example, if *Firm A* is in trouble and defaults on its obligations, *Bank A* does not incur any losses since it is compensated by *Bank B*. However, if *Bank B* also defaults on its obligations to *Bank A*, *Bank A* is forced to write-off the credit to the firm, incurring capital losses. If these losses are large enough, *Bank A* will default as well on its obligations to other banks. The initially small problem spreads through the entire network. A popular example to illustrate this problem [e.g. Cont, 2015] is the ring structure depicted in Panel A of Figure 4.A.1. Arrows denote the direction of the exposure while the figures denote the size. A default by A imposes losses on B, which when defaulting, imposes losses on C. Hence, difficulties of one agent spread to other agents in the market.

In contrast, a market structure with a central counterparty (CCP) can avoid this problem of contagion. As its name says, a CCP is the counterparty to every market participant. Going back to the first example, both banks *A* and *B* again agree on the terms of the CDS. However, instead of executing the trade themselves they go to the CCP which intercepts itself between the two. *Bank A* now pays the coupon to and is insured against credit losses by the CCP. At the same time, *Bank B* receives coupon payments from the CCP while insuring it against credit losses of *Firm A*. The CCP also imposes margin requirements. The advantage of this market structure is that a default by *Bank B* can be absorbed by the CCP (with proper risk management) such that *Bank A* remains unaffected. Additionally, in a market with more than two participants, a CCP can reduce gross exposure via netting (cf. Cont and Kokholm [2014]). This is illustrated in Panel B of Figure 4.A.1.

In practice, a CCP has several so-called members. These are large dealer banks. They are the only market participants that interact directly with the CCP. If some other entity would like to trade, it has to go through one of the members. For every trade, both parties are required to post initial margins (IM). Additional collateral may be needed, e.g. depending on the relative size of the position. The purpose of this collateral is to absorb losses and inject liquidity, in case a member defaults. During the lifetime of a derivative contract, members additionally receive and post variation margin (VM) on a daily basis, reflecting changing market valuations of the underlying contracts. Using VMs, a CCP transfers market losses/gains of a derivative contract to its members. A CCP itself is not affected by changing market valuations because for every position, it has an off-setting position.

The main advantage of a CCP comes from its improved risk management. If a member defaults, it has several "lines of defense" which are summarized in its default waterfall. First, losses are absorbed by the IMs. If this is not sufficient, part of a CCP's own capital is next in line ("skin in the game"). Its purpose is to incentivize the CCP to conduct proper risk management. If this still is not enough to absorb the losses there is an insurance fund (IF) available to which each clearing member has to contribute. If the defaulting members share of the IF is still not sufficient, the remaining fund may be used. These lines of defenses are common across CCPs, details may vary, however. For more details and the adequacy of the waterfall see Cont [2015]; Faruqui et al. [2018].

Figure 4.A.1: Stylized Derivatives Market without/with a CCP



a) Panel A: Without CCP

b) Panel B: With CCP

These figures show stylized versions of derivative market structures. Panel a depicts a market where agents A, B, and C are directly exposed to each other. Panel b depicts a market where all the exposures between agents A, B, and C are intercepted and netted by the CCP.

4.A.2 History

This subsection describes the history of CCPs and how this affects the current regulatory environment. Clearing houses have existed, in some form, since at least 1853 in the USA. They were used by banks in New York City to settle daily claims against each other and to act as a lender of last resort. Gorton [1985] argues that this institution was the predecessor of the New York Fed. In its current form, as financial institutions in the derivative markets CCPs remained small actors for most of the 20th century. Nevertheless, there were three failures of CCPs in the 1970s and '80s. For more details see Bignon and Vuillemey [2020].

CCPs came into the public spotlight again in the aftermath of the Great Financial Crisis. At the time of its failure, Lehman Brothers had large derivative positions outstanding with several clearing houses across the world (e.g. an interest rate swap portfolio with the London Clearing House with a notional of around $9 trillion). These clearing houses were able to unwind the contracts using initial margins posted without any losses to its members. Faruqui et al. [2018] discuss this episode in more detail. On the other hand, the failure of a big institution in the (uncleared) OTC market for CDS had a severe impact. When AIG, a large issuer of CDS, failed in 2008, markets panicked. Due to the opaque nature of the OTC CDS market it was impossible to distinguish which banks and financial institutions had direct (or indirect) exposure to AIG. To avoid any further spillovers from defaults and to prevent credit markets from shutting down, the US government decided to bail out AIG [Commission et al., 2011].

After the GFC, regulators acknowledged the different performances of the two derivative markets with respect to their market structure. They drew the conclusion that cleared derivative markets perform better and are safer during times of crisis and hence, central clearing should be encouraged. This idea was implemented in the Dodd-Frank Act in 2010 in the US and somewhat later in the European Market Infrastructure Regulation (EMIR) in 2012 in Europe. Key points of this regulations were mandatory clearing requirements for several derivative classes such as interest rate swaps and index CDS (but importantly, not single-name CDS) as well as mandatory reporting requirements of all derivative trades to trade repositories. Hence, the legislation encouraged central clearing and caused a shift in trading activities away from OTC markets to CCPs (also for derivative classes not directly affected by the regulation). At the same time, derivative markets saw a reduction in the total outstanding notional due to more standardization of contracts which enabled more trade compression as well as netting of exposures within clearing houses, see e.g. Gündüz et al. [2017].

Figure 4.A.2: Outstanding CDS by Counterparty for Financial Firms

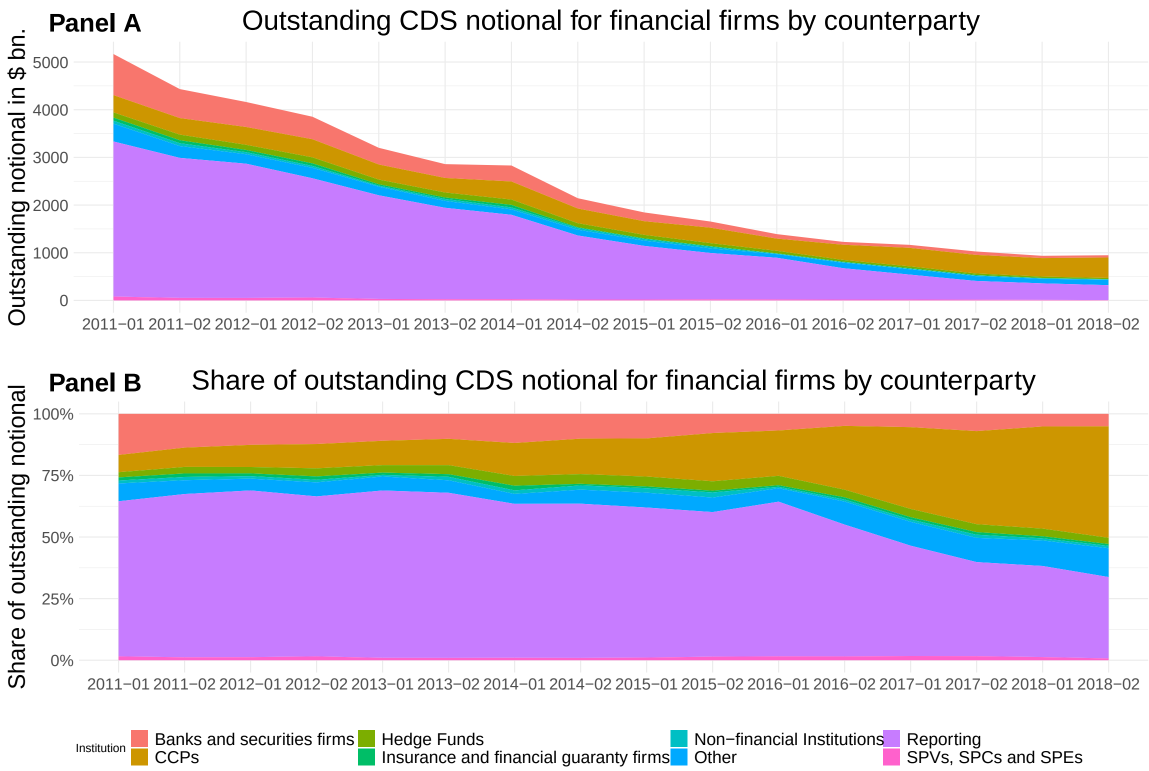
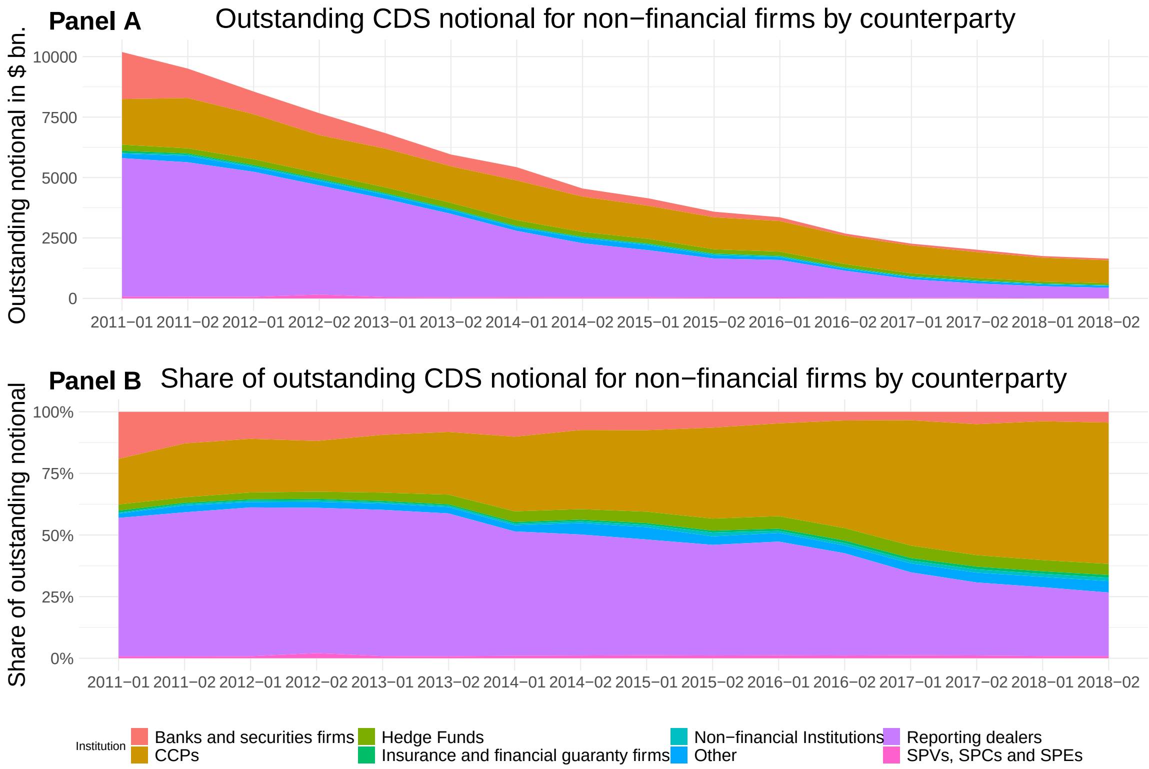


Figure 4.A.3: Outstanding CDS by Counterparty for Non-financial Firms



4.B Data appendix

Figure 4.B.1: Number of newly eligible reference entities by quarter

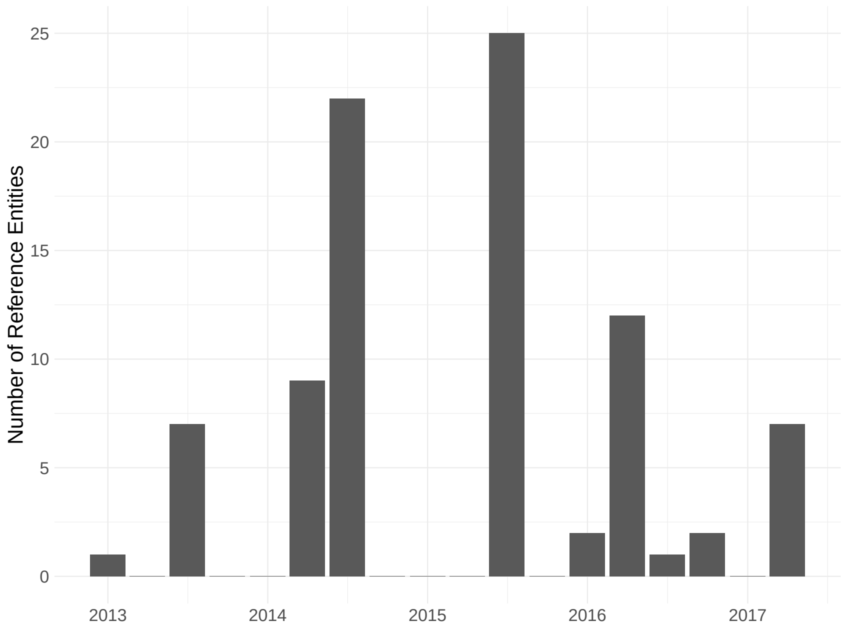


Table 4.B.1: Clearing Eligiblity Dates

Clearing date	N	Reference Entity
25/03/2013	1	Mondelez International
30/09/2013	7	Avon Products, Block Financial, Caterpiller Financial Services Corporation, Ford Motor Company, Genworth Holdings, Boeing, The Gap,
27/06/2014	9	Ally Financial, Chesapeake Energy Corp, D.R. Horton, Frontier Communications, L Brands, Lennar Corp, Louisiana-Pacific Corp, PulteGroup, Royal Caribbean Cruises
11/07/2014	9	American Axle & Manufacturing, Avis Budget Group, Bombardier, Brunswick Corp, Dish DBS Corp, HCA, Hertz, New York Times, Universal Health Services

31/07/2014	11	Amkor Technology, Beam Suntory, Dean Foods, Host Hotels & Resorts, Kinder Morgan, Liberty Interactive, Olin Corp, Sealed Air Corp, Tenet Healthcare Corp, AES, Goodyear
04/08/2014	12	Cooper Tire & Rubber, CSC Holdings, Dillard's, Levi Strauss, Navient, Nova Chemicals Corp, NRG Energy, Pactiv, Smithfield Foods, Neiman Marcus Group, United Rentals (North America), Vulcan Materials Company
20/07/2015	9	AK Steel Corp, Beazer Homes USA, Domtar Corp, General Motors, K. Hovnanian Enterprises, KB Home, Meritor, United States Steel Corp, Weyerhaeuser Company
03/08/2015	10	Advanced Micro Devices, Enbridge, Iheartcommunications, J.C. Penney, MGM Resorts International, Rite Aid Corp, Supervalue, Teck Resources, The McClatchy Company, Toys "R" US
17/08/2015	6	CIT Group, Community Health Systems, First Data Corp, Level3 Communication, Radian Group, Sprint Communications
08/02/2016	1	General Electric
14/03/2016	1	Chubb Limited
30/05/2016	7	Best Buy, Chubb INA Holdings, Exelon Generation Company, Hess Corp, Johnson & Johnson, Owens-Illinois, Packaging Corporation of America
13/06/2016	4	Assured Guaranty Municipal Corp, Diamond Offshore Drilling, Ford Motor Credit Company, MGIC Investment Corp
27/06/2016	1	FIS Data Systems
04/07/2016	1	MGM Growth Properties Operating Partnership
14/11/2016	1	iStar
12/12/2016	1	Lamb Weston Holdings
03/04/2017	1	Uniti Group
10/04/2017	6	Bank of America, Citigroup, JPMorgan Chase, Morgan Stanley, Goldman Sachs, Wells Fargo

Table 4.B.2: Variable definitions and sources

Variable	Definition	Source
Firm balance sheet		
$Cash$	Natural logarithm of cash holdings	Compustat
$Capex$	Natural logarithm of capital expenditures	Compustat
$Revenues$	Natural logarithm of revenues	Compustat
ROA	Return on average assets (winsorized at the 1% and 99% level)	Compustat
$Total\ Assets$	Natural logarithm of total assets	Compustat
$Total\ Debt$	Natural logarithm of total debt	Compustat
$Long{-}term\ Debt$	Natural logarithm of debt with maturity >1 year	Compustat
$Short{-}term\ Debt$	Natural logarithm of debt with maturity ≤ 1 year	Compustat
$Leverage$	Ratio of total debt to total assets	Compustat
$Equity$	Natural logarithm of book value of common equity	Compustat
$Stock\ price$	Natural logarithm of close quote of company's traded stocks	Compustat
$Employment$	Natural logarithm of number of employees	Compustat
$z{-}score$	Altman z-score	Authors' calculation, Compustat
$Gross\ PPE$	Natural logarithm of gross expenditures for properties, plants and equipment	Compustat
$Net\ PPE$	Natural logarithm of net expenditures for properties, plants and equipment	Compustat
Debt and CDS markets		
$CDS\ spread$	Spread of 5-year CDS contract denominated in US dollar with CR credit event (winsorized at the 1% and 99% level)	Markit
$Outstanding\ bond\ debt$	Natural logarithm of outstanding bond volume	TRACE
$Bond\ issuance$	Ratio between newly issued debt and total level of pre-period assets	Compustat
$Bond\ yield$	Volume-weighted average of yields of all bonds that are dollar denominated, senior debt, have a fixed coupon and maturity >1 year	TRACE
$CDS\ notional$	Natural logarithm of outstanding notional value of open CDS contracts	DTCC
$CDS - bond\ basis$	Difference between CDS spread and synthetic CDS spread obtained from bond yields (winsorized at the 1% and 99% level)	Markit
Mutual fund holdings		
$Bond\ volume$	Sum of bond holdings issued by the same firm measured in percent of total net assets of the respective fund	WRDS
$CDS\ volume$	Sum of CDS holdings written on the same firm measured in percent of total net assets of the respective fund	WRDS
$CDS\ volume\ (short)$	Sum of CDS holdings written on the same firm measured in percent of total net assets of the respective fund (only short/selling positions)	WRDS
Syndicated loans		
$Loans$	The sum of the credit volume of all syndicated loans extended to a specific borrower	Dealscan
$Credit\ lines$	The sum of the credit volume of syndicated loans extended to a specific borrower which classify as credit lines	Dealscan
$Term\ loans$	The sum of the credit volume of syndicated loans extended to a specific borrower which classify as term loans	Dealscan

Table 4.B.3: Descriptive statistics – matched sample

The table presents descriptive statistics of all relevant LHS and control variables for the matched sample. The statistics are calculated from 2012Q1 to 2019Q2.

Variable	Mean	Median	Std. Dev.	Min	Max
Cash	6.4500	6.4151	1.6359	0.5092	10.6656
Capex	5.5676	5.5787	1.6178	-2.3539	10.2808
Revenues	7.7372	7.6732	1.0006	5.1855	10.6445
ROA	0.0101	0.0092	0.0175	-0.0629	0.0736
Leverage	0.4211	0.3920	0.2661	0.0608	3.1794
Total Assets	9.4610	9.2484	1.1828	7.1261	12.4959
Total Debt	8.4529	8.3086	1.2438	5.7043	11.9736
Z-Score	3.9293	3.0963	3.3447	-2.6337	29.4609
CDS Spread	243.46	149.84	322.26	1.0000	2249.91
Bond Issuance	0.0945	0.0391	0.1630	0.0000	0.9786
Bond Yield	4.3258	3.8120	2.5022	-1.9820	32.64
CDS Notional	16.3762	16.3412	0.9592	14.7318	19.2316
CDS-Bond Basis	-30.610	-28.502	86.601	-204.30	170.60
Gross PPE	8.9040	8.9371	1.2598	4.0955	11.7000
Net PPE	8.1733	8.1005	1.5160	2.9707	11.5081
Employment	3.4695	3.5499	1.2009	0.4479	5.8081
Stock Price	3.5103	3.6014	0.9400	0.3500	9.0653

4.C Elastic bond supply

In the previous section we fixed supply at some value S. Although this approach allows for tractability when computing equilibrium prices, we cannot make any statements on how the level of firm debt varies when CC is introduced, which is a main focus of the empirical part of this paper. Hence, we loosen the initial assumptions of fixed bond supply. Assume that bond supply is given by a linear function

$$S(p) = \alpha p + \beta$$

with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$. That is, there is some fixed component β corresponding to outstanding debt and a variable component αp corresponding to rollovers and new debt issues increasing in prices. A higher bond price is equivalent to a lower interest rate for a bond with no coupon payments. All else equals this means that a firm will issue more bonds when interest rates are low, which is a reasonable assumption. Again, we can solve for the bond price by equating bond supply and demand:

$$\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\Big(1-\overline{\pi}-p-\frac{c_b}{2}+d\frac{\Delta}{2}\Big)+\frac{\lambda}{c_b}\Big(1-p-\frac{c_b}{2}-\overline{\pi})\Big)\right)\frac{\Delta}{2}+\frac{1}{2}\frac{\lambda}{c_b}\Big(1-\overline{\pi}--p\frac{c_b}{2}\Big)^2\right)=S(p)$$

Proposition 3 gives the equilibrium price.

Proposition 3. *When bond supply is given by $S(p) = \alpha p + \beta$ with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$ the equilibrium bond price is given by*

$$\hat{p} = 1-\overline{\pi}-\frac{c_b}{2}+\frac{\Delta}{2}+\Delta\frac{c_b}{\lambda}\alpha-\sqrt{\Big(\frac{\Delta}{2}+\Delta\frac{c_b}{\lambda}\alpha\Big)^2-d\frac{\Delta^2}{4}+2\Delta\frac{c_b}{\lambda}\gamma}$$

where $\gamma \equiv \alpha(1-\frac{c_b}{2}-\overline{\pi})+\beta$.
Proof: *See Appendix 4.D.*

We can compute the equilibrium bond price in closed form. Note that setting $\alpha = 0$ and $\beta = S$ collapses the result to the case with fixed bond supply. Similar to Proposition 2, we can show that $\hat{p}$ decreases when d decreases.

Proposition 4. *A lower default probability d decreases the bond price $\hat{p}$ when bond supply is an elastic, linear function of p. The total amount of bonds issued decreases, when d decreases. If*

$\alpha(1-\overline{\pi}-\frac{c_b}{2})+\beta > S$ the price decrease with elastic supply is smaller than the price decrease when supply is fixed.
Proof: *See Appendix 4.D.*

The second part of Proposition 4 follows directly from the fact that the bond supply function has a positive slope. Lower bond prices make it more expensive for firms to issue bonds. Hence, they reduce their debt level. The third part of the proposition follows from the first two. The decline in d lowers bond prices. However, part of this decline is absorbed by the firm which issues fewer bonds. Hence, the price does not have to fall as much as would be the case with fixed supply. However, this only holds if the fixed part of the supply β is not too large. To give an intuition for this condition consider the case, where β is very large. Then, the change in d can barely have an effect on overall bond supply.
We can show that a decrease in d decreases both bond prices and quantities for a more general set of bond supply functions $S(\cdot)$. First define total bond demand $D()$ as a function of p and d. Note that $D(p,d)$ is increasing in d: $D(p,d) > D(p,\hat{d}) \forall d > \hat{d}$ and continuous. Then for any continuous, positively sloped bond supply function $S(p)$ we can define the excess demand function $D(p,d)-S(p)$ which equals zero at the equilibrium price p^* and is strictly decreasing. Then it follows from a simple continuity argument that for all $\hat{d} < d$ in a neighbourhood around d there exists $\hat{p} < p^*$ such that $D(\hat{p},\hat{d})-S(\hat{p}) = 0$. From the fact that supply is an increasing function (demand is a decreasing function) it also follows that the total amount of bonds decreases.

4.D Proofs

4.D.1 Proposition 1 - Proof

With $c_{CDS} = 0$, the equilibrium CDS price is $q^* = (1-d)\overline{\pi}$ and the equilibrium bond price is

$$p^* = 1 - \overline{\pi} - \frac{c_b}{2} + \frac{\Delta}{2} - \sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}$$

Proof: We first determine the equilibrium CDS price q^*. Solving $V_{buyCDS,i} = 0$ and $V_{buyCDS,i} = 0$ with $c_{CDS} = 0$ yields $q_i = (1-d)\pi_i$. At price q_i, investor i is indifferent between buying and selling CDS. Hence, all investors j with $\pi_j > \pi_i$ ($\pi_j < \pi_i$) get a positive payoff from buying (selling) the CDS, independent of μ_j.
Lastly, in equilibrium supply of CDS must equal demand. For that purpose, we follow Oehmke and Zawadowski [2015]. Consider some $\overline{\mu} < \infty$. Equality between supply and demand is then given at $q^* = (1-d)\overline{\pi}$ where half of all investors (with $\pi_i < \overline{\pi}$) sell the CDS whereas the other have buys the CDS. Letting $\overline{\mu}$ go to infinity yields the desired result. Given that the CDS market is infinitely large we can take q^* as given to solve for p^*. Again we must equal supply and demand where bond demand is given by the area of the "Buy bonds" trapezoid and the "Basis" triangle in Figure 4.4.1 multiplied by the conditional density $\frac{1}{\Delta}$. The market clearing condition is given by:

$$\frac{1}{\Delta}\left(\left(\frac{\lambda}{c_b}\left(1 - \overline{\pi} - p - \frac{c_b}{2} + d\frac{\Delta}{2}\right) + \frac{\lambda}{c_b}\left(1 - p - \frac{c_b}{2} - \overline{\pi})\right)\right)\frac{\Delta}{2} + \frac{1}{2}\frac{\lambda}{c_b}\left(1 - \overline{\pi} - -p\frac{c_b}{2}\right)^2\right) = S.$$

Substituting $x \equiv 1 - \overline{\pi} - p - \frac{c_b}{2}$ yields a quadratic equation in x. Using standard methods we can then solve for x which gives

$$\begin{aligned} x &= -\frac{\Delta}{2} + \sqrt{\frac{\Delta^2}{2}(1-d) + 2\Delta S\frac{c_b}{\lambda}} \\ \Leftrightarrow 1 - \overline{\pi} - p - \frac{c_b}{2} &= -\frac{\Delta}{2} + \sqrt{\frac{\Delta^2}{2}(1-d) + 2\Delta S\frac{c_b}{\lambda}} \end{aligned}$$

Solving for p yields the desired result. □

4.D.2 Proposition 3 - Proof

When bond supply is given by $S(p) = \alpha p + \beta$ with $S(p) > 0 \forall p \in [0,1]$ and $\alpha > 0$ the equilibrium bond price is given by

$$\hat{p} = 1 - \overline{\pi} - \frac{c_b}{2} + \frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha - \sqrt{\Big(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\Big)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}$$

where $\gamma \equiv \alpha(1 - \frac{c_b}{2} - \overline{\pi}) + \beta$.

Proof: The proof of Proposition 3 follows the same structure as in Proposition 1. The argument regarding the price of the CDS does not change. Only when solving for $\hat{p}$ we must consider that S is now a function of p. Hence the market clearing condition is given by

$$\frac{1}{\Delta}\Bigg(\Bigg(\frac{\lambda}{c_b}\Big(1 - \overline{\pi} - p - \frac{c_b}{2} + d\frac{\Delta}{2}\Big) + \frac{\lambda}{c_b}\Big(1 - p - \frac{c_b}{2} - \overline{\pi})\Big)\Bigg)\frac{\Delta}{2} + \frac{1}{2}\frac{\lambda}{c_b}\Big(1 - \overline{\pi} - -p\frac{c_b}{2}\Big)^2\Bigg) = S(p)$$
$$= \alpha p + \beta.$$

We can rearrange the right hand side such that

$$S(p) = \alpha\Big(p - 1 + \overline{\pi} + \frac{c_b}{2}\Big) + \alpha\Big(1 - \overline{\pi} - \frac{c_b}{2}\Big) + \beta.$$

We define $\gamma \equiv \alpha\Big(1 - \overline{\pi} - \frac{c_b}{2}\Big) + \beta$ and substitute $x \equiv 1 - \overline{\pi} - p - \frac{c_b}{2}$ into the market clearing condition and solve the resulting quadratic equation in x using standard methods. Lastly, we solve for p which yields the desired result. □

4.D.3 Proposition 4 - Proof

A lower default probability d decreases the bond price $\hat{p}$ when bond supply is an elastic, linear function of p. The total amount of bonds issued decreases, when d decreases. If $\alpha(1 - \overline{\pi} - \frac{c_b}{2}) + \beta > S$ the price decrease with elastic supply is smaller than the price decrease when supply is fixed.

Proof: To show the first part of the proposition we compute the partial derivative of $\hat{p}$ w.r.t. d:

$$\frac{\partial \hat{p}}{\partial d} = \frac{\Delta^2}{8\sqrt{\left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}} > 0$$

To show the second part of the proposition consider two equilibria i and ii with varying d such that $d_i < d_{ii}$. From above we then know that $p_i < p_{ii}$ and $S(p_i) < S(p_{ii})$ because $\alpha > 0$. For the last part of the proposition compare $\frac{\partial \hat{p}}{\partial d}$ and $\frac{\partial p^*}{\partial d}$:

$$\begin{aligned}
\frac{\partial \hat{p}}{\partial d} &< \frac{\partial p^*}{\partial d} \\
\Leftrightarrow \frac{\Delta^2}{8\sqrt{\left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma}} &< \frac{\Delta^2}{8\sqrt{\frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S}} \\
\Leftrightarrow \frac{\Delta^2}{4}(1-d) + 2\frac{c_b}{\lambda}\Delta S &< \left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4} + 2\Delta\frac{c_b}{\lambda}\gamma
\end{aligned}$$

Note that $\frac{\Delta^2}{4}(1-d) < \left(\frac{\Delta}{2} + \Delta\frac{c_b}{\lambda}\alpha\right)^2 - d\frac{\Delta^2}{4}$. Hence, a sufficient condition for the inequality to hold is

$$\begin{aligned}
2\frac{c_b}{\lambda}\Delta S &< 2\Delta\frac{c_b}{\lambda}\gamma \\
\Leftrightarrow S &< \gamma \\
\Leftrightarrow S &< \alpha(1 - \overline{\pi} - \frac{c_b}{2}) + \beta
\end{aligned}$$

The desired result follows. $\square$

4.E Numerical example

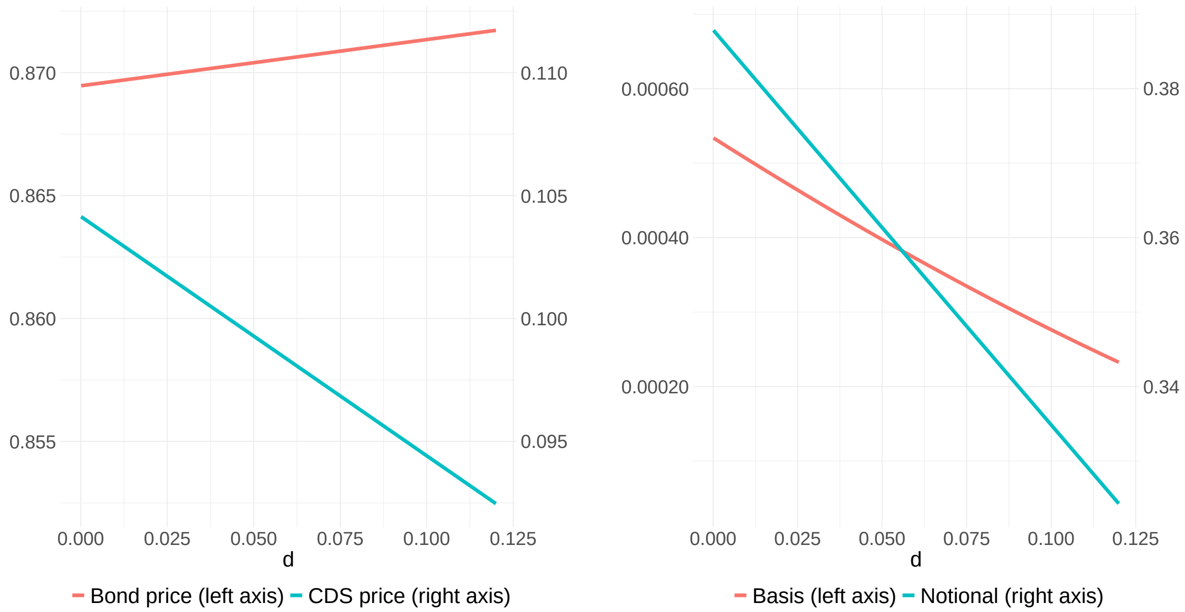
In this section we discuss the effect of CC (a simultaneous decrease in d and an increase in c_{CDS}) in the model with positive c_{CDS}. Since we cannot solve the model analytically, we instead rely on an numerical example to illustrate the dynamics of the model. All results are qualitatively robust to changes in the basic parameters. We take the values for these parameters from Oehmke and Zawadowski [2015] with $\lambda = 0.2$, $\overline{\pi} = 0.1$, $\Delta = 0.12$, $c_b = 0.02$ and $S = 0.2$. For clarity of exposition we discuss the case with fixed supply. All results carry over to the case with elastic supply, albeit attenuated.

Before discussing the joint change in d and c_{CDS} we consider only isolated changes in these variables. First, we analyze decreasing the market maker's default probability d. We coined this channel the *arbitrage channel*. The lower counterparty risk raises the attractiveness of CDS contracts. This generates an inflow to the sell-side of the CDS market away from investors who have previously been buying the bond. Hence, both CDS prices and demand go up. Then in equilibrium it must hold that bond prices fall (with falling demand for bonds). In a version of the model with elastic bond supply, the total amount of bonds outstanding then also falls.

This is exactly what we find in Figure 4.E.1. First, consider the left panel (with $c_{CDS} = 0.006$). As in the cases discussed in Section 4.4 with $c_{CDS} = 0$, we can clearly see that the sign of change regarding prices remains the same. When d decreases, the price of the CDS contract increases, as before. The likelihood that the market maker honors the contract increases if the firm defaults and hence, the value and the price of the contract increases. The increased price changes the attractiveness of selling the CDS contract relative to buying the bond. To clear markets in equilibrium the price (interest rate) of the bond must therefore decrease (increase) such that it remains attractive to a sufficient amount of investors.

This change in prices is accompanied by a change in the amount of CDS contracts traded (bond supply remains fixed, otherwise it would decrease). First, consider the CDS notional (measure of CDS contracts bought/sold). Clearly, a decrease in d increases the total notional. CDS contracts become more attractive, in particular to investors who previously chose to hold cash. Optimistic investors (low π_i) now receive a higher price when selling the contract. More pessimistic investors also benefit because it is more likely that they will be repayed in case the firm defaults. Hence, the measure of investors who buy and sell CDS increases. The change in the measure of investors conducting the negative basis trade is *ex ante* unclear. A higher CDS price makes it less attractive to buy a CDS and a bond simultaneously, all else equal. The cost of hedging increases the price of the entire bundle. However, the bond price declines as well in equilibrium. This may counteract the higher hedging costs with higher expected returns. Additionally, a lower default probability d increases the expected payout if the firm defaults. As it turns out, the latter to effects dominate the first such that the total measure of investors in the basis trade increases, consistent with our proposed channel.

Figure 4.E.1: Numerical example - varying d



These figures show comparative statics of various equilibrium outcomes in response to a change in the market maker default probability d.

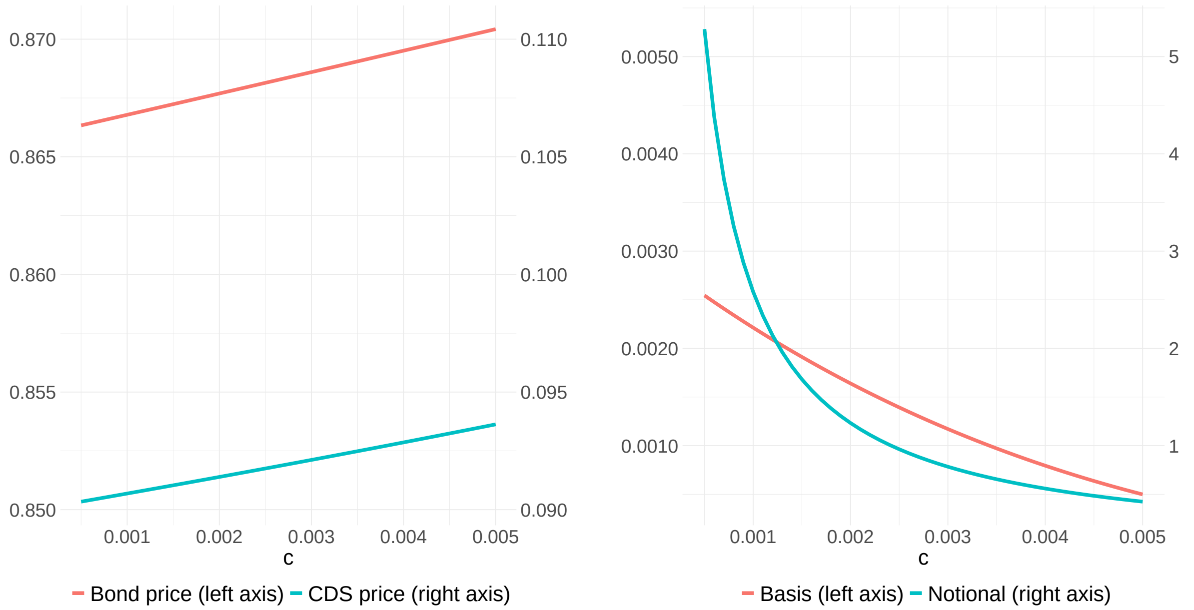
Next, we move on to analyze increases in c_{CDS} which corresponds to our proposed *hedging channel* where higher trading costs induce people to leave the CDS market and to switch to either bonds or cash. Since former CDS sellers have two alternatives (cash and buying bonds), but former CDS buyers only have one (cash), there are more sellers leaving the market than buyers. This creates an upward pressure on the CDS price. As some CDS sellers become bond buyers, there is upward pressure on the bond price which leads to fewer people conducting the hedged trade (the basis trade) of jointly buying the bond and the CDS contract. In sum, CDS prices go up and CDS demand

goes down.
Figure 4.E.2 illustrates these relationships. First, consider the left panel which shows bond and CDS prices. Clearly, bond prices increase when c_{CDS} increases. Higher trading costs of the CDS decrease the expected payoff of the contract relative to buying bonds. Then in equilibrium, the price of bonds must increase to clear markets. At the same time, the price of the CDS contract also increases with c_{CDS}. Investors demand to be compensated for higher trading costs when buying/selling a CDS contract. Hence, both prices increase when c_{CDS} decreases.

Moving on to the right panel we note that both the notional and the measure of investors doing the basis trade decrease when c_{CDS} increases. The notional decreases because holding cash or buying bonds become relatively more attractive relative to selling CDS contracts (similarly holding cash becomes more attractive relative to buying CDS contracts). This holds particularly true for investors with shorter investment horizon (small μ_i). Hence, fewer investors are willing to buy/sell CDS. Note that for very small c_{CDS} we converge back to the baseline model (outlined in Section 4.4) with an infinite notional. The same argument holds for the measure of investors conducting the basis trade. Fewer are willing to bear the higher trading costs as it lowers their expected payoff (even with higher prices) when their investment horizon is short.

Taking stock we note that both a decrease in d and an increase in c_{CDS} increases the price of the CDS. Assuming that there are no non-linearities at play a joint change in these two variables should therefore increase the price of the CDS as well. Regarding the other outcomes, however, effects go in different directions. Bond prices decreases with lower d while they increase with higher c_{CDS}. Similarly, the total notional and the measure of basis investors increases when d decreases while the opposite is true when c_{CDS} increases. Hence, it is *ex ante* unclear which of the two effects prevails under a joint change. In particular, the relative size of changes in the variables should determine which effect is stronger.

Figure 4.E.2: Numerical example - varying c_{CDS}



These figures show comparative statics of various equilibrium outcomes in response to a change in the CDS trading costs c_{CDS}.

4.F Calibrating the model

In Section 4.4 we showed how CC, captured by a simultaneous decrease in the market maker's default probability and an increase in the CDS' trading costs, can generate an increase in the CDS spread. Furthermore, we argued that the model can generate a stable bond price as well as a decrease in the amount of outstanding bonds (when bond supply is elastic) which is consistent with our empirical findings. In this section, we want to ask what changes in the market maker's default probability and CDS' trading costs are qualitatively and quantitatively consistent with these findings given a calibrated set of parameters.

We use moments from our data set to estimate the parameter values.[41] For $\overline{\pi}$ (the average expected probability of a bond's default) we choose firm's average default probability implied by its average CDS spread according to Hull's formula[42] between 2010

[41]We focus on the case where bond supply is fixed to abstract from the issue of choosing an appropriate functional form for the bond supply curve.

[42]Hull's formula computes the probability of default (PD) with respect to the CDS/interest rate spread: $PD = 1 - exp(\frac{-m \cdot spread}{1-LGD})$ where m denotes the maturity in years.

and 2012. Δ (the range of believes about $\overline{\pi}$) is computed from the corresponding standard deviation in implied probabilities. We take c_{CDS} (the cost of trading CDS contracts) from Wojtowicz [2014] who estimates the average bid-ask spread for CDS. The bid-ask spread for bonds (c_b) is the average bid-ask spread in our bond sample. In our model, d represents the probability of default an investor. We choose the spread between the one year LIBOR rate and the one year treasury rate between 2010 and 2013 to compute the average implied probability of default in the interbank market (which includes all the major traders and dealer banks). This is a common measure in the literature to capture the risk of default in the banking sector. Lastly, λ (the Poisson rate governing maturity) is chosen to match the maturity of a CDS contract of 5 years. Table 4.F.1 presents the estimates.

Table 4.F.1: Parameter estimates

The table presents the parameter values used in calibrating the model and their sources.

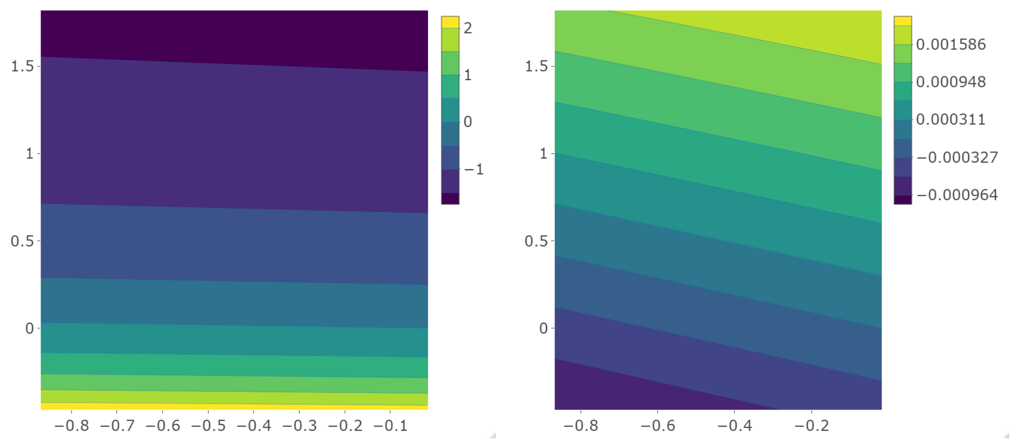
Parameter	Estimate	Source
$\overline{\pi}$	0.129	Markit: average implied probability of default for firms between 2010 and 2013
Δ	0.112	Markit: standard deviation of implied probability of default for firms between 2010 and 2013
c_b	0.0065	TRACE: average bid-ask spread for bonds in our sample
c_{CDS}	0.0011	Wojtowicz [2014]
d	0.035	St. Louis Fed: implied probability of default from the one year LIBOR-treasury rate spread
λ	0.2	5 year maturity of CDS

Using these parameter values as our baseline, we can then simulate effects on prices and quantities when d and c_{CDS} change jointly. Since the CDS spread moves upward unambiguously and we assume the bond supply to be fixed, we investigate the effect on the CDS notional and the bond price. Figure 4.F.1 presents the contour plots for the changes in the bond price and the outstanding notional (relative to the baseline model). In both panels the horizontal axis denotes the change in d (in percent) while the vertical axis denotes the change in c_{CDS} (in percent), i.e. the point (0,0) denotes the baseline model with values for d and c_{CDS} as in Table 4.F.1.

First, consider Panel 4.F.1a. Darker colors denote a stronger decrease in the notional. Holding the change in d fixed, a stronger increase in c_{CDS} leads to a stronger decrease in the total outstanding notional. On the other hand, holding c_{CDS} fixed, a stronger decrease in d decreases the notional by less. In our empirical exercise we found that the outstanding CDS notional only marginally decreased if at all (Table 4.5.1). This outcome is not informative about the change in d while being consistent with an increase of c_{CDS}

by a relatively small amount (5% to 10%).
Panel 4.F.1b shows the change in the bond price. Darker colors denote a decrease while lighter colors denote an increase in the bond price. Again, values on the axis are expressed as percentages. In Table 4.F.1 we found a slight increase in the yield (i.e. a decrease in the bond price) if any change at all. For the model to be consistent with this result and a small increase in c_{CDS} deduced from Panel A, we require a relatively strong decrease in d (roughly 30-50%).

Figure 4.F.1: Change in the notional and bondprice when varying d and c_{CDS}



a) Change in notional **b)** Change in bond price

These figures show the impact on the calibrated model of jointly varying the market maker default probability d on the x-axis and the trading costs c_{CDS} on the y-axis. Changes on the axis are measured in relative terms such that -0.5 corresponds to a reduction by 50% and 1 corresponds to an increase by 100%. The lower right corner in both graphs represents the benchmark with the values for d and c_{CDS} calibrated using the pre-treatment sample.

Hence, we can infer from the model that our empirical observations are consistent with a relatively strong decrease in d by around 30-50% while the cost of trading c_{CDS} only increased by a relatively small amount (around 5% to 10%). The arbitrage channel is therefore outweighing the hedging channel by a significant margin. This is an important contribution to the understanding of the CCP reform. From a financial stability point of view, the reform seems to have provoked a large decrease in the (perceived) counterparty risk on the market for only a small increase in the trading costs (cf. Duffie et al. [2015]). These changes, however, imply non-trivial and adverse consequences for the funding situation of non-financial firms. Thus, we document a trade-off between financial stability and real economic activity to be inherent to the CCP reform.

4.G Robustness checks

Table 4.G.1: Balance sheet impact of clearing eligibility – unmatched sample

The table presents results of running regression specification 4.1. The estimation is based on an unmatched sample of 72 treated and 148 control firms from 2012Q1 to 2019Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.041***	-0.056***	-0.016***	-0.004	-0.026*
	(0.010)	(0.012)	(0.006)	(0.005)	(0.015)
Matched sample	No	No	No	No	No
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	6411	6445	6447	6411	6091
adj. R^2 (within)	0.76	0.69	0.86	0.81	0.75

Table 4.G.2: Balance sheet impact of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.023***	-0.017**	-0.013**	0.000	-0.017
	(0.008)	(0.008)	(0.005)	(0.003)	(0.016)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	5244	5242	5244	5244	4941
adj. R^2 (within)	0.85	0.82	0.90	0.90	0.79

Table 4.G.3: Market impact of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) CDS spread	(2) Outstanding bond debt	(3) Bond issuance	(4) Bond yield	(5) CDS notional	(6) CDS-bond basis
$Eligibility_i$	14.49**	-0.022**	-0.013	0.412	-0.019	4.94
	(6.57)	(0.010)	(0.008)	(0.344)	(0.040)	(4.81)
Matched sample	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3213	1945	3289	2030	2160	2485
adj. R^2 (within)	0.78	0.91	0.28	0.05	0.25	0.54

Table 4.G.4: Real effects of clearing eligibility – matched sample starting in 2011

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Gross PPE	(2) Net PPE	(3) Employment	(4) ROA	(5) Stock price
$Eligibility_i$	-0.01*	-0.01*	-0.002	-0.025	-0.042**
	(0.005)	(0.005)	(0.001)	(0.016)	(0.020)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	4092	5851	5244	5077	748
adj. R^2 (within)	0.90	0.91	0.05	0.80	0.63

Table 4.G.5: Overall loans – matched sample starting in 2011

The table presents results of running regression specifications 4.6 and 4.7. The estimation is based on a matched sample of 69 treated and 69 control firms from 2011Q1 to 2019Q4, where the matching uses information from 2009Q1 to 2010Q4. We identify 496 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	-7.275	-7.954	0.065	0.083	0.021	0.038
	(7.722)	(9.322)	(0.096)	(0.110)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	52,484	52,484	52,484	52,484	52,484	52,484
adj. R^2 (within)	0.507	0.445	0.575	0.516	0.729	0.706

Table 4.G.6: Balance sheet impact of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Total debt	(2) Long-term debt	(3) Total assets	(4) Leverage	(5) Equity
$Eligibility_i$	-0.035***	-0.043***	-0.011	-0.003	0.012
	(0.009)	(0.010)	(0.007)	(0.005)	(0.021)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	2779	2786	2786	2779	2467
adj. R^2 (within)	0.81	0.79	0.85	0.85	0.71

Table 4.G.7: Market impact of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. In columns (1), (5), and (6) the z-score is an additional control variable. In columns (2) and (4) the average bond rating, bid-ask spread and return are additional control variables. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) CDS spread	(2) Outstanding bond debt	(3) Bond issuance	(4) Bond yield	(5) CDS notional	(6) CDS-bond basis
$Eligibility_i$	26.82***	-0.027***	-0.027***	0.325	-0.015	-0.81
	(8.06)	(0.012)	(0.009)	(0.242)	(0.044)	(5.03)
Matched sample	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1725	1578	1827	1623	1305	1309
adj. R^2 (within)	0.77	0.94	0.27	0.10	0.27	0.54

Table 4.G.8: Real effects of clearing eligibility – alternative matching with pre-quarter values

The table presents results of running regression specification 4.1. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Gross PPE	(2) Net PPE	(3) Employment	(4) ROA	(5) Stock price
$Eligibility_i$	-0.01	-0.01	-0.001	-0.061**	-0.036
	(0.006)	(0.007)	(0.001)	(0.031)	(0.023)
Matched sample	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes
N	1930	2757	2786	2689	552
adj. R^2 (within)	0.85	0.84	0.01	0.67	0.48

Table 4.G.9: Overall loans – alternative matching with pre-quarter values

The table presents results of running regression specifications 4.6 and 4.7. The estimation is based on a matched sample of 47 treated and 47 control firms from 2012Q1 to 2019Q4, where the matching exclusively uses information from the quarter directly preceding treatment. We identify 430 lenders in the data set. $Eligibility_i$ is a dummy that takes the value 1 starting from the quarter that a firm becomes eligible for central clearing. The firm-level control variables (lagged by one quarter) are cash, capex, revenues, ROA, leverage, total assets and total debt. N refers to the total number of observations. Standard errors clustered at the firm-level are in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

	(1) Exposure	(2) Exposure	(3) Log Exposure	(4) Log Exposure	(5) Scaled Exposure	(6) Scaled Exposure
$Eligibility_i$	20.456***	26.618**	0.274***	0.337***	0.033*	0.040*
	(7.722)	(9.322)	(0.096)	(0.110)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Time FE	Yes	No	Yes	No	Yes	No
Bank×Time FE	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	39,305	39,305	39,305	39,305	39,305	39,305
adj. R^2 (within)	0.463	0.379	0.487	0.399	0.676	0.626

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