Bank opacity - patterns and implications*

Stefan Avdjiev† and Maximilian Jager‡

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Abstract

We investigate the patterns and implications of bank opacity in Europe using a rich bank-level data set. Employing a novel event study methodology, we document that public data releases on banks' exposures to individual countries and sectors contain information not previously priced by equity and CDS markets. Bank opacity is highest for European periphery banks' sovereign exposures and European core banks' private sector exposures. Underestimation of banks' credit risk by markets is associated with lower funding costs and higher wholesale borrowing (for all banks) as well as with greater risk taking and higher profitability (for European periphery banks).

JEL classification: F34, G21, G28

Keywords: bank opacity, asymmetric information, event study, credit risk, asset markets

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†Corresponding author. Bank for International Settlements, Centralbahnplatz 2, 4051 Basel, Switzerland, e-mail: Stefan.Avdjiev@bis.org.

‡Frankfurt School of Finance & Management, Adickesallee 32-34, 60322 Frankfurt, Germany, e-mail: m.jager@fs.de.

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 our 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 decreased (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

[1]Details on the construction of this measure are presented in Section 2.

last hypothesis.

After establishing the existence of bank opacity, we dig deeper into its patterns across bank nationalities, borrowing sectors, time periods and news types ("good news" versus "bad news"). 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 markets reacted strongly to "bad news" (i.e. news that expected losses were higher than existing estimates), their directional responses to "good news" (i.e. news that expected losses were lower than previously estimated) were not significant. Finally, 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 × 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 × 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 2 provides information on the data sources and the construction of our key variables. Section 3 presents our event study analysis that documents the existence and patterns of bank opacity. Section 4 presents our empirical analysis of the implication of bank opacity. Section 5 concludes.

2 Data

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:

$$CSEL_{i,j,k,t} = \frac{EAD_{i,j,k,t} \cdot PD_{j,k,t} \cdot LGD_{j,k,t}}{TC_{i,t}}, \tag{1}$$

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

[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.

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:

$$EL_{i,t} = \sum_{j,k} CSEL_{i,j,k,t} \tag{2}$$

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:

$$\widehat{CSEL}_{i,j,k,t} = \frac{EAD_{i,j,k,t^*} \cdot PD_{j,k,t} \cdot LGD_{j,k,t}}{TC_{i,t}}, \tag{3}$$

where t^* denotes the latest date for which there is publicly available information on the EAD. Table 1 lists each t^* date in our sample, along with the corresponding data release dates (T).

Table 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:

$$\widehat{EL}_{i,t} = \sum_{j,k} \widehat{CSEL}_{i,j,k,t} \tag{4}$$

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

$$EL\_Gap_{i,t} = EL_{i,t} - \widehat{EL}_{i,t} \tag{5}$$

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)*). There is no further distinction available between industries in "Corporates" or between mortgages and consumer credit in "Retail". We complement the EBA data with information 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 A.1.

[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.

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

$$PD_{j,k,t} = 1 - exp(-Spread_{j,k,t} * Mat), \tag{6}$$

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 collect data on bank CDS spreads from Markit and on bank equity prices from Thomson Reuters' Eikon.

[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.

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.

2.2 Data summary

Table 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 2: Descriptive statistics

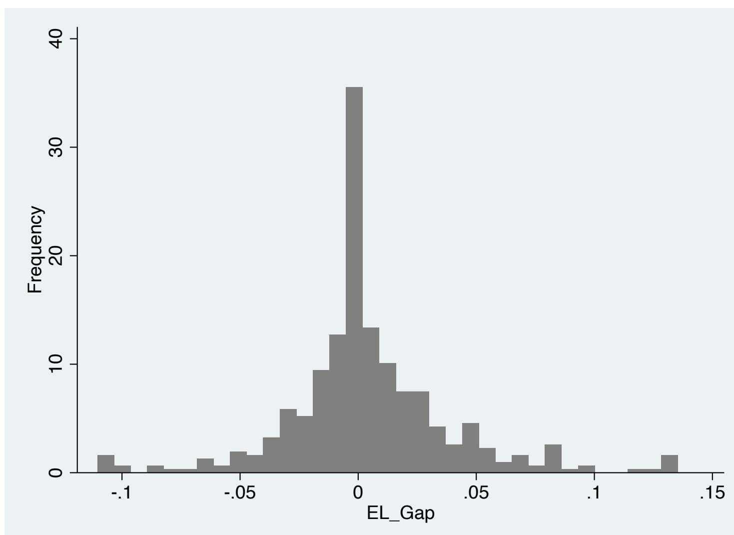
	Mean	Median	Std. Dev.	Min	Max
$EL_{i,t}$	0.29	0.28	0.11	0.09	1.06
$\widehat{EL}_{i,t}$	0.28	0.28	0.10	0.09	0.59
$EL\_Gap_{i,t}$	0.00	0.00	0.04	-0.11	0.14
$Total\ Assets\ (log)$	19.21	19.06	1.48	14.82	21.99
$Tier1\ Ratio$	0.15	0.13	0.08	0.07	0.65
$ROAA$ (%)	0.18	0.23	0.65	-2.33	1.88
$Net\ Interest\ Margin$ (%)	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 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 wellcapitalized, 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.

Figure 1 plots the histogram of $EL\_Gap_{i,t}$. The distribution is well-behaved. Most importantly, there are neither large outliers, nor any significant asymmetry between positive and negative values. This makes the $EL\_Gap_{i,t}$ a well-suited variable for the analyses in Section 4.

Figure 1: Histogram of $EL\_Gap_{i,t}$



Note: This figure displays a histogram of all values of $EL\_Gap_{i,t}$ for all banks in our benchmark sample (from 2012Q4 to 2018Q2).

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 2a, 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

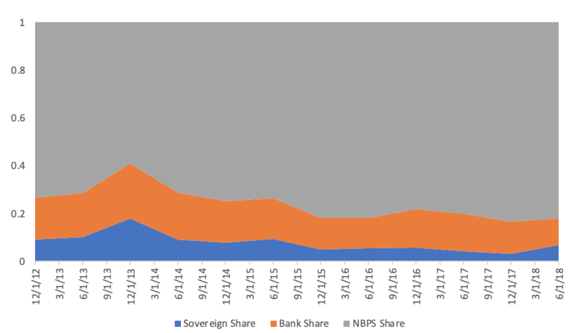
[8] We aggregate $\widehat{CSEL}_{i,j,k,t}$ across all counterparty countries to obtain sector-specific estimated expected losses for each bank at each point in time: $\widehat{SEL}_{i,k,t} = \sum_j \widehat{CSEL}_{i,j,k,t}$.

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.

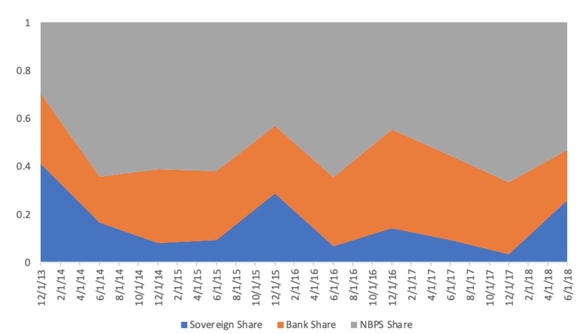
In turn, the right-hand panel of Figure 2b decomposes the expected loss gap ($EL\_Gap_{i,t}$) into its sectoral components. While the NBP sector still accounts for the largest share of the variance of the expected loss gap variable, its relative importance is considerably smaller than in the decomposition 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 3.

Figure 2: 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.

[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.

3 The impact of public information disclosures

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:

$$U(p_1) = -e^{-\lambda(p_1 - p_0)};\ \lambda > 0. \tag{7}$$

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

[10] See Appendix B for the proof.

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 information 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

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

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.

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):

$$\Delta \widehat{EL}_{i,T^{l,s}} = \widehat{EL}_{i,T+l} - \widehat{EL}_{i,T-s} \tag{8}$$

$$\Delta AP_{i,T^{l,s}} = log(AP_{i,T+l}) - log(AP_{i,T-s}). \tag{9}$$

where $\Delta \widehat{EL}_{i,T^{l,s}}$ 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.

$\Delta AP_{i,T^{l,s}}$ 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:

$$\Delta AP_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,T^{l,s}} + \epsilon_i. \tag{10}$$

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

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

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 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 in Equation 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.

3.3 Baseline results

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

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 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 2 and 3, 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".

Table 4: Event study results – sector, bank nationality, directional and time splits

Panel A – splits for CDS

	(1) ΔCDS Sectoral	(2) ΔCDS Sectoral	(3) ΔCDS Sectoral	(4) ΔCDS Core	(5) ΔCDS Periphery	(6) ΔCDS Positive	(7) ΔCDS Negative	(8) ΔCDS Early	(9) ΔCDS Late
$\Delta\widehat{EL}_{i,t}$				0.66***	0.44***	0.42***	-0.09	0.51***	0.11
				(0.01)	(0.00)	(0.00)	(0.89)	(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***	-0.03**	-0.07***	-0.04***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
R^2	0.09	0.02	0.00	0.05	0.16	0.14	0.00	0.16	0.00
N	172	172	172	100	72	79	93	84	88

Panel B – splits for stocks

	(1) ΔEquity Sectoral	(2) ΔEquity Sectoral	(3) ΔEquity Sectoral	(4) ΔEquity Core	(5) ΔEquity Periphery	(6) ΔEquity Positive	(7) ΔEquity Negative	(8) ΔEquity Early	(9) ΔEquity Late
$\Delta EL^*_{i,t}$				-0.14*	-0.29***	-0.31***	0.05	-0.26***	0.05
				(0.06)	(0.01)	(0.00)	(0.84)	(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**	0.03***	0.03***	0.01	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.15	0.00	0.00	0.02	0.13	0.29	0.00	0.15	0.00
N	172	172	172	100	72	79	93	84	88

Note: Columns (1)-(3) of panel A show the results of estimating the event study regression $\Delta CDS_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{SEL}_{i,k,T^{l,s}} + \epsilon_i$. Columns (4) and (5) show the results of estimating the event study regression $\Delta CDS_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,k,T^{l,s}} + \epsilon_i$ 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 $\Delta CDS_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,k,T^{l,s}} + \epsilon_i$ separately for positive ("bad news") and negative ("good news") values of $\widehat{EL}_{i,k,T^{l,s}}$. Columns (8) and (9) show the results of estimating the event study regression $\Delta CDS_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{EL}_{i,k,T^{l,s}} + \epsilon_i$ 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.

[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 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 $\Delta CDS_{i,T^{l,s}} = \alpha + \beta \cdot \Delta\widehat{SEL}_{i,k,T^{l,s}} + \epsilon_i$. 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.

Columns 4 and 5 of Table 4 contain the results for the bank nationality sub-samples (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 test for the existence of a potential asymmetry between the market's reaction to good versus bad news about the riskiness of banks' assets (Black [1976] and many others). To investigate this, we split the sample in two parts, depending on whether $\widehat{EL}_{i,k,T^{l,s}}$ is positive or negative. A positive (negative) value of that variable indicates that the actual riskiness of a bank's lending portfolio revealed by the EBA release is higher (lower) than the existing market estimates, and is therefore classified as "bad news" ("good news"). The results in columns (6) and (7) of Table 4 provide evidence of asymmetric market behaviour for both asset classes we examine. More concretely, "bad news" (i.e. news indicating that expected losses are higher than existing estimates) were associated with significant re-pricing moves (in the respective expected directions) in equity and CDS markets. By contrast, the responses of both of these markets to "good news" (i.e. news indicating that expected losses are lower than previously estimated) were not statistically significant.

It is important to note that the above set of results does not imply that "good news" were completely ignored by markets. The constant terms in the "good news" sub-samples are highly significant for both, CDS and equity markets. This suggests that while "good news" do not trigger directional adjustments in banks' CDS spreads and equity prices, they do push equity prices up and CDS spreads down via their uncertainty resolution effect.

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 (8) and (9) of Table 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 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.

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 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.

4 Implications of bank opacity

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:

$$\begin{aligned} Interest\_rate_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \\ \gamma' X_{i,t-1} + BankFE + FundFE + TimeFE + \epsilon_{i,t}, \end{aligned} \tag{11}$$

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 11 with several variables capturing MMF funding volumes:

$$Fund\_vol_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \gamma' X_{i,t-1} + BankFE + FundFE + TimeFE + \epsilon_{i,t}, \tag{12}$$

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 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 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

Table 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.

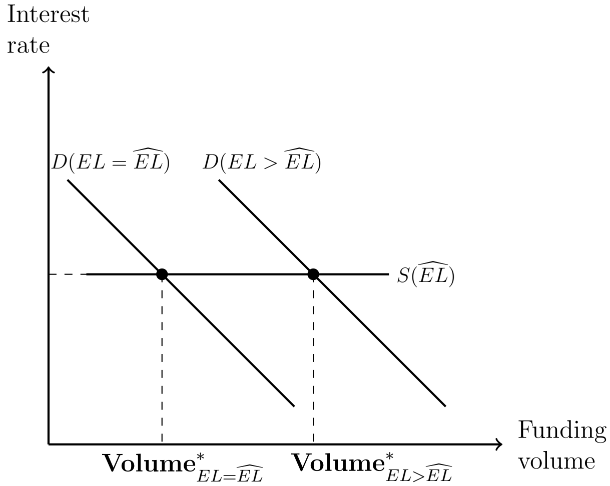
market is underestimating their expected losses, banks increase their MMF funding by 0.5% of their total assets.

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 11 and 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 6. The coefficients in all columns are very close (in terms of both, magnitude and significance) to their counterparts in Panel A of Table 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 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 3.[16]

[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.

Figure 3: 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 2.1.

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

$$\begin{aligned} Loan\_growth_{i,j,t} = \beta \cdot EL\_Gap_{i,t-1} + \theta \cdot EL\_Gap_{i,t-1} \times FirmType_j + \\ \gamma' X_{i,t-1} + BankFE + Borrower \times TimeFE + \epsilon_{i,t}, \end{aligned} \tag{13}$$

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

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 13 are presented in column (1a) of Panel A in Table 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 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 (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 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

[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]).

Table 7: Loans to the non-bank private sector

Panel A – all banks

	(1a)	(1b)	(2)	(3)
$EL\_Gap_{i,t-1}$	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

	(1a)	(1b)	(2)	(3)
$EL\_Gap_{i,t-1}$	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

	(1a)	(1b)	(2)	(3)
$EL\_Gap_{i,t-1}$	-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.

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 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 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:

$$\Delta Y_{i,t+h} = \beta \cdot EL\_Gap_{i,t} + \gamma' X_{i,t} + BankFE + TimeFE + \epsilon_{i,t+h}, \tag{14}$$

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 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 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

[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 7), which covers syndicated loans to the non-bank private sector.

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 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									
	$\Delta L_{i,t+1}$	$\Delta L_{i,t+2}$	$\Delta L_{i,t+3}$	$\Delta DS_{i,t+1}$	$\Delta DS_{i,t+2}$	$\Delta DS_{i,t+3}$	$\Delta NIM_{i,t+1}$	$\Delta NIM_{i,t+2}$	$\Delta NIM_{i,t+3}$
$EL\_Gap_{i,t}$	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									
	$\Delta L_{i,t+1}$	$\Delta L_{i,t+2}$	$\Delta L_{i,t+3}$	$\Delta DS_{i,t+1}$	$\Delta DS_{i,t+2}$	$\Delta DS_{i,t+3}$	$\Delta NIM_{i,t+1}$	$\Delta NIM_{i,t+2}$	$\Delta NIM_{i,t+3}$
$EL\_Gap_{i,t}$	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.

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.

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Appendix A

Additional information on the data used in the empirical analysis

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 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

[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.

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.

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.

A.3 List of banks in data set

Table A1: 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

Appendix 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

$$U(P) = -e^{-\lambda(p_1-p_0)},\ \lambda > 0. \tag{15}$$

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

$$\begin{aligned} E(U(p_1)) =& \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} -e^{-\lambda(p_1-p_0)} e^{-\frac{(p_1-\mu)^2}{2\sigma^2}} dp_1 \\ =& \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} -e^{-(\lambda(p_1-p_0)+\frac{(p_1-\mu)^2}{2\sigma^2})} dp_1. \end{aligned} \tag{16}$$

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

$$E(U(p_1)) = -\frac{e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2}-p_0)}}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(\frac{(p_1-\mu+\lambda\sigma^2)^2}{2\sigma^2})} dp_1. \tag{17}$$

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

$$E(U(p_1)) = -e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2}-p_0)} \cdot \underbrace{\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(p_1-\hat{\mu})^2)}{2\sigma^2}} dp_1}_{=1}, \tag{18}$$

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:

$$E(U(p_1)) = -e^{-\lambda(\mu - \frac{\lambda\sigma^2}{2} - p_0)}, \tag{19}$$

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 $(1 - \overline{PD}) - \frac{\lambda}{2}\sigma^2$.