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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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European banks after the global financial crisis: Peak accumulated losses, twin crises and business models*

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Abstract

This paper takes stock of European banks' accumulated losses since 2007 and relates these to bank characteristics. In line with previous studies, we find that large, market-oriented banks were particularly hit by the 2007-2009 global financial crisis whereas smaller, retail-oriented banks weathered these years relatively well. In subsequent years, however, the picture reversed and retail-oriented banks were most affected. Over the entire period, medium-sized banks suffered most losses and often needed state aid. This suggests that measures to contain systemic risk, such as capital surcharges and bail-in requirements, are as relevant for these institutions as they are for the largest banks.

Keywords*:* Bank profitability, Business model, Financial crisis.
JEL classifications*:* G01, G21.

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1 Introduction

European banks were hit hard by the 2007-2009 global financial crisis and the subsequent European (sovereign) debt crisis (Figure 1). Although losses are still accumulating in some banks, the experience so far provides useful information about the order of magnitude of losses in a systemic event. Historical losses provide a reference point for adequate levels of capital or, more broadly, loss absorbing capacity. Indeed, banks' historical losses have been an important input for the calibration of international regulatory standards.[1]

The crisis has also revived policymakers' interest in bank characteristics. Some banks weathered the crisis better than others, which suggests that business models may be relevant to explain banks' performance in times of distress. Recent regulatory measures, such as Basel 3, are likely to affect bank characteristics and activities (EBA, 2015). For instance, the largest banks have to hold a systemic capital surcharge while banks that rely on short-term wholesale funding are particularly affected by the new liquidity requirements. Structural reforms, such as new resolution regimes and ring-fencing, may have a major impact on banks' organizational and funding structures. Bank business models have also been incorporated in supervisory frameworks more directly. For instance, the European Single Supervisory Mechanism (SSM) included "Business models and profitability drivers" as a focus area in 2016 and 2017 (ECB, 2016).

[FIGURE 1 Bank earnings 2006-2016: a double dip]

This paper documents European banks' performance in the 2007-2016 period and explores the nexus between bank characteristics and fragility. We focus on banks with total assets larger than EUR 30 bn, which captures almost the entire banking system in the European Union. Performance is measured at the institution-specific level by peak accumulated losses. We characterize banks by size categories and business models. Using factor analysis, we identify two main business models: large investment banks, which suffered most during the global financial crisis, and retail banks which were particularly hit in the European debt crisis.

[1] See, for instance, analyses of historical losses by the Basel Committee (BCBS, 2010) and the Financial Stability Board (FSB, 2015).

The paper is organized as follows. Section 2 briefly discusses recent studies on bank performance and bank characteristics. Section 3 presents an analysis of bank losses, including a first assessment of differences between size categories. Section 4 further explores differences across banks by relating losses to business models. Section 5 evaluates the results and discusses implications for loss absorbing capacity. Section 6 concludes.

2 Bank performance and bank characteristics: recent literature

Recent empirical studies have investigated the relationship between bank characteristics and vulnerabilities in the recent crisis, using a variety of techniques.

Altunbas et al. (2011) analyse a large set of European and US banks, focusing on the 2007-2009 global financial crisis. They conclude that banks that were hit most – measured by capital and liquidity support and systemic risk – were typically large institutions with low capital ratios and a strong dependence on short-term market funding. By contrast, banks that weathered the crisis well had a large retail deposit base and diverse income sources. Beltratti and Stulz (2012) also focus on the global financial crisis, using stock market performance as a measure of distress for a large set of listed banks from advanced and emerging economies. They find that high leverage, reliance on short-term funding and relatively high profits just before the crisis contributed to a bad performance in subsequent years. Demirgüç-Kunt and Huizinga (2010) conclude that, in the run-up to the crisis, particularly large and fast-growing banks had a large proportion of non-interest income and were depending on wholesale funding. These banks were more profitable than other banks, but also turned out to be more vulnerable during the crisis (see also Detragiache et al., 2018). Pouw and Kakes (2013) provide further evidence that banks relying on wholesale funding were relatively profitable before the crisis.

The Liikanen (2012) report, which was written by a high-level expert group established by the European Commission, considered the performance of European banks in the global financial crisis. Although the report concludes that the European banking system was severely hit across the board, it also notes that large banks were affected more than small banks and that specific characteristics – reliance on wholesale funding, high leverage, a market-oriented business model – explain why some banks were less resilient than others.

Laeven et al. (2014) relate bank performance in the global financial crisis to various risk indicators and conclude that large banks' are particularly vulnerable if they have low levels of capital and unstable funding. Moreover, large banks give rise to more systemic risk – beyond their own individual risk – if they are organizationally complex and engaged in market based-activities. This higher systemic risk also explains why it is typically expected that large banks are more likely to receive state support than smaller banks, as reflected by rating agencies' support ratings (Poghosyan et al., 2016).

Some studies focus on differences in banks' behavioural responses to explain their performance in the crisis. Detragiache et al. (2010) conclude that the extent to which European banks' preserved their profitability can be explained by their ability to contain the rise in non-performing loans, cut operating costs, and aggressively reduce assets and dependence on wholesale funding. Shehzad et al. (2010) find that concentrated bank ownership is positively related to banks' ability to take action, particularly in jurisdictions with weak shareholder protection rights.

Ayadi and De Groen (2014) identify business models for a set of EU banks, using cluster analysis. They distinguish four types: investment banks, wholesale banks, diversified retail and focused retail banks. They consider the period 2006-2013, which covers the global financial crisis and most of the European debt crisis, and observe changes in business model performance over time. In particular, wholesale banks suffered high losses in the 2007-2009 period, but recovered in subsequent years. By contrast, focused retail banks did relatively well in the global financial crisis, but performed very badly in more recent years. Lucas et al. (2016) also apply cluster analysis over the entire post-2007 period and identify six business models. The main focus of their analysis is how different types of banks deal with low interest rates.

Overall, studies focusing on the 2007-2009 global financial crisis typically find that large banks with relatively low capital ratios and significant wholesale activities have been hit most. Ayadi and De Groen (2014) are an exception in that they consider almost the entire post-2007 period and observe a shift in performance (return on assets, return on equity, cost-to-income) with retail banks underperforming in more recent years.

Our analysis covers the entire period from 2007 onwards, while we use peak accumulated bank losses (PAL) as a measure of bank performance. An advantage of using historical losses, compared to e.g. stock prices, is that we can include both listed and non-listed banks. In addition, (accumulated) losses can be relatively easily translated into implications for the required loss-absorbing capacity. Regarding bank characteristics, we look at bank size – measured by total assets – but we also identify business models using factor analysis, following similar approaches by De Haan (2003) and Van Ewijk and Arnold (2014).

3 Historical losses 2007-2016

Annual data for EU banks are obtained from the SNL database. We only consider banks at the consolidated level, i.e. individual branches and subsidiaries are excluded. Losses are measured by comprehensive income, a broad definition of income which also includes unrealized losses that are not directly reflected in the profit and loss statement. The latter is important to capture losses that are booked through a write-down of assets. Most of our analysis focuses on a core set of banks with at least EUR 30 bn total assets. This cut-off corresponds to the size criterion used by the European Single Supervisory Mechanism (SSM) to identify significant institutions and covers the bulk of the banking system. A further discussion of data and definitions is presented in Annex A.

3.1 Breakdown into size categories

Figure 2 presents a breakdown of banks' aggregated losses – i.e. the bottom line in Figure 1 – into balance sheet size categories. In the international financial crisis, losses were largely concentrated at the largest banks (balance sheets exceeding EUR 500 bn) while after 2009, medium-sized and small banks were most affected.

[FIGURE 2 Largest banks hit first, smaller banks later]

Table 1 presents stylized facts for the total group of banks in our sample as well as by size category. Whereas the largest banks represent about two thirds of the total banking system's assets, they only cover about half of the losses. Medium-sized banks experienced almost the same amount of losses in absolute terms, while their combined assets are significantly lower. A significant proportion of the losses are concentrated in the so-called GIIPS countries (Greece, Ireland, Italy, Portugal and

Spain, as well as Cyprus), which have been most hit by the crisis. To some extent, losses of medium-sized and GIIPS-based banks can be explained by cyclical factors, which is illustrated by the relatively large credit gap at the onset of the crisis in 2007. In Section 4, we further explore whether performance is related to other characteristics, captured by bank business models.

Medium-sized banks also received relatively more state aid, both in terms of the proportion of banks receiving aid and the nominal volume of support. Again, a large share of aid is concentrated in banks from GIIPS countries. The annual pattern of state aid mirrors that of losses, peaking around 2008-2009 and 2011-2012 (Annex 1). The connection between losses and aid by category illustrates that state support is not just provided to the largest banks, which are typically considered too-big-to fail, but also to medium-sized banks, implying that the latter may be prone to similar moral hazard incentives.[2]

[TABLE 1 Stylized different size classes EU banks]

3.2 Bank-specific performance: peak accumulated loss

We characterize each bank's individual performance by its peak accumulated loss (PAL). PAL is calculated as a bank's total income over a time interval, within the 2007-2016 sample period, that minimizes accumulated profits (or, equivalently, maximizes accumulated losses).[3] Because the PAL interval can also include years with positive income and exclude years of negative income, the overall number is lower than aggregate losses in each category. Figure 3 shows that PAL is negative for 87 percent of the banks in our core set, which means that the vast majority experienced a loss in at least one or more years. In about one quarter of the cases, PAL is more than 3 percent of total assets and for one fifth it is more than 8 percent of risk-weighted assets. These are important reference points for the minimum leverage ratio and risk-weighted pillar 1 requirements under the new Basel 3 rules.

Previous studies have documented bank losses in systemic crises, with an order of magnitude similar to our findings. The UK's Independent Commission on Banking (2011), the ESRB (2014)

[2] A relevant aspect here is to what extent state aid is accompanied by compensating measures ("remedies"), which can be imposed by the European Commission to address competition concerns.

[3] See Annex 1 for a detailed explanation and references to previous studies using PAL.

and Houben (2016) present cumulative losses for EU banks, which – taking into account that they consider shorter periods – are in line with our results. Strah et al. (2013) present accumulated losses in the recent crisis for large US banks, leading to capital erosion up to 12 percent of RWA. BCBS (2010) presents PAL estimates for previous crisis episodes, with peak losses of up to about 12 percent of RWA for Finnish banks during the Nordic banking crisis and almost 25 percent of RWA for Korean banks during the Asian financial crisis.[4] The FSB (2015) presents PAL estimates for 13 Global Systemically Important Banks (G-SIBs) in Europe, the US and Japan – comparable with our category of banks larger than EUR 500 bn – which suffered losses up to about 13 percent of RWA and 5 percent of TA.

[FIGURE 3 Distribution peak accumulated losses across banks]

3.3 Caveats

The losses took place under circumstances that have changed in recent years. This is inevitable, but causes upward and downward biases compared to how losses might have evolved under today's circumstances:

- Regulation has been strengthened and banks have become better capitalized, which increases their ability to deal with a crisis and contain losses.[5] Loss ratios in this paper are measured using the data in banks' financial statements, published under three international capital accords (Basel 1-3). Definitions of total exposures – to be used for the leverage ratio – and RWA have become more conservative under Basel 3. Under the new regulatory framework, loss ratios would probably have been lower than under the old framework.[6]

[4] Drees and Pazarbasioglu (1998) present detailed data on performance for the Scandinavian countries during the Nordic banking crisis in the early 1990s. In terms of income before taxes, accumulated losses as a percentage of TA in Finland were 6 percent for commercial banks and almost 17 percent for savings banks; in Norway accumulated losses were 7 and 2 percent for these categories, in Sweden 4 and 5 percent, respectively. Note that these are aggregates by banking group; the variation across individual banks within each group is likely to be higher.

[5] See the annual progress report of the Financial Stability Board on the implementation and effects of regulatory reforms (FSB, 2017).

[6] More generally, more stringent regulation and supervision is likely to reduce banking risks (Klomp en De Haan, 2011), which would contain losses in a crisis. Better capitalization may also help to contain the rise in funding costs.

- However, other aspects work in the opposite direction.[7] Some banks are still making losses, implying that loss ratios may go up further than our data show. Moreover, losses have been contained by interventions by governments and central banks, including capital and funding support to banks as well as macroeconomic stabilization policies. It is far from certain whether governments will have the willingness and sufficient financial resources for similar support measures in a future crisis.

4 Bank losses and business models

In this section, we further explore the relationship between losses and bank-specific variables beyond size, by identifying business models based on a variety of bank characteristics. In addition, we analyse how business models interact with the timing of losses (i.e. global financial crisis versus European debt crisis) and banks' home jurisdiction (i.e. GIIPS versus non-GIIPS).

4.1 Identification of bank business models

We apply factor analysis to 15 bank characteristics that have also been used in previous business model studies (e.g. Altunbas et al., 2011; Ayadi and De Groen, 2014; Lucas et al., 2016):

Size: total assets (logs).
Sources of income (as a proportion of total operating income):
- Net interest income
- Fees & commissions
- Trade income

Liquid assets (as a proportion of total assets):
- Cash and cash equivalents
- Securities

Interconnectedness with the banking system (as a proportion total assets):
- Bank deposits
- Net loans to banks
- Total net loans

Market orientation (as a proportion of total assets):
- Derivatives held for trading
- Assets held for trading

Risk mix: market and operational risk as a proportion of credit risk (logs).
Capitalization:

[7] In addition to the aspects mentioned here, the assumptions underlying our calculations are such that they are likely to underestimate loss ratios. This is because we use annual data (quarterly data would result in a sharper definition of the PAL interval, as losses in the second half of 2008 would not be compensated with positive income in the first half of that year) and because losses are expressed as a percentage of assets in the first year of a PAL interval (using average assets over the PAL interval leads to lower loss ratios as banks with high losses often shrink over time, see Annex A).

Equity ratio (proportion of total assets)
Tier 1 ratio (proportion of risk-weighted assets)
Dependence on wholesale funding: loan-to-deposit ratio.

These elements are included in a factor analysis (for details, see Annex B). Because not all variables are available for all banks, the sample is reduced to 69 institutions.[8] The loss performance of these institutions are likely to be representative for the entire sample, however, as the length and initial years of PAL intervals are very similar (Figure A2 in Annex A).

We find two factors, which we interpret as business models:

- *Factor 1: Big investment banks.* Factor 1 is relatively large for big banks that hold a lot of securities, derivatives and assets for trading and have a relatively large exposure to market risk.
- *Factor 2: Retail banks.* Factor 2 is relatively large for relatively small banks that are especially dependent on interest income, have little other income from fees or trading, and hold a lot of liquid assets.

For brevity, we will refer to the two types of business models as Factor 1 banks and Factor 2 banks, respectively, when discussing the regression results. Overall, Factor 1 banks are more market oriented while Factor 2 banks are closer to traditional intermediaries.

4.2 Regression results

Panel A of Table 2 presents the outcomes of linear regressions, to investigate the relationship between PAL and business models Factor1 and Factor2, respectively. The first regression equation is:

$$PAL_i = a_0 + a_1 Factor1_i + a_2 Factor2_i \qquad (1)$$

where *i* stands for bank *i*. The estimation period is 2007-2016.

[8] We also considered other characteristics, such as a distinction between retail loans, mortgage loans and corporate loans. Although these variables are likely to be relevant for the identification of business models, they are only available for a very small number of banks, which would shrink our sample too much.

The significantly negative value of -2.46 estimated for the constant term a_1 in Equation (1) indicates that PAL is typically negative, as expected. Factor1 has a significantly positive impact (0.98), which implies that big investment banks' losses tend to be lower than the sample average.

[TABLE 2 Regression results]

Our next step is to analyse whether differences between business models also reflect variation over time, particularly between the global financial crisis and the European debt crisis. This time split is motivated by the twin crises periods observed in Section 3. We investigate this by adding interaction terms in Equation (2), where Period1 is a dummy that is 1 if the first year of the PAL interval falls in the years up to and including 2009 and 0 if the fist loss year is 2010 or later:

$$PAL_i = a_0 + a_1 Factor1_i + a_2 Factor2_i + a_3 Factor1_i \times Period1 + a_4 Factor2_i \times Period1 + a_5 Period1 \quad (2)$$

The estimated value for a_3 is significantly negative (-1.88), which suggests that big investment banks were mostly hit during the global financial crisis. Hence, the fact that such banks' losses tended to be lower than the sample average is mainly due to the fact that they were not hit much by the European debt crisis. This is confirmed by a further analysis of average marginal effects of Factor1 and Factor2 in both sub-periods, presented in Panel B of Table 2. These marginal effects show that only the impact of Factor1 in Period2, i.e. the period from 2010 onwards, is statistically significant (+2.08). This finding suggest that the better performance of big investment banks over the period as a whole is driven by their relatively low losses since 2010.

The regression outcomes can also be illustrated graphically. Note that each bank has a score for Factor 1 and for Factor 2 (which both, by construction, have mean 0). If Factor 1 exceeds Factor 2, a bank is more an investment bank than a retail bank, and vice versa. We call a bank an investment (retail) bank if the difference between its values for Factor 1 and Factor 2 lies above (below) the interquartile range. If the difference lies within the interquartile range, the type of bank is considered indeterminate or hybrid. In Figure 4, we show how total losses developed for these three categories. The aggregate pattern is very similar to Figure 2, with somewhat lower losses because of the smaller sample. Investment banks suffered greatest losses in 2008, while retail banks were hardly hit at that time. Retail banks suffered losses after 2009, when investment banks experienced a second but smaller wave of loss. The losses of the indeterminate type of banks developed similarly to those of investment banks.

[FIGURE 4 Losses by business model category]

Our regression results are broadly in line with previous studies discussed in Section 2. Most of these studies focus on the 2007-2009 global financial crisis and conclude that large, wholesale-oriented banks were hit most while retail-oriented banks performed relatively well. When the entire post-2007 period is considered, however, the picture changes. We find that retail banks were particularly hit in the second stage of the crisis, like Ayadi and De Groen (2014), and also show that these banks had the worst performance over the entire sample period.

The underperformance of Factor2 banks, especially since 2010, may be largely attributed to the European debt crisis rather than just business models. This crisis particularly affected the so-called GIIPS countries (Greece, Ireland, Italy, Portugal, Spain) and Cyprus. To further investigate this, we first add interaction terms for GIIPS in Equation 3 in Table 2, where GIIPS is a dummy that is one for banks from the GIIPS countries and Cyprus, and 0 otherwise:

$$PAL_i = a_0 + a_1 Factor1_i + a_2 Factor2_i + a_3 Factor1_i \times GIIPS_i + a_4 Factor2_i \times GIIPS_i + a_5 GIIPS_i \qquad (3)$$

The significantly negative estimated value for a_5 (-4.47) confirms that GIIPS banks were hit most over the entire sample. Moreover, the estimated value for a_4 (-6.24) shows that the underperformance of GIIPS banks was strongest for retail banks. This is confirmed by the average marginal effects of Factor1 and Factor2 in both groups of countries, presented in Panel B of Table 2. These marginal effects show that only the impact of Factor2 banks in GIIPS countries is statistically significant (-6.27).

Overall, we find that Factor1 banks were mostly hit by the 2007-2009 global financial crisis and Factor2 banks in the post-2009 years, while at the same time these results are largely driven by banks from the GIIPS countries (including Cyprus). A relevant issue is whether specific characteristics to GIIPS banks other than business models play a role. In particular, large sovereign exposures have played a role in the European debt crisis, leading to negative sovereign-bank feedback loops (Bekooij et al., 2006). However, the difference between Factor1 and Factor2 banks can also be observed *within* the sample of GIIPS banks, where retail banks underperformed investment banks, implying that business models are relevant to explain banks' performance.

5 Implications for loss absorbing capacity

More loss absorbing capacity is an essential element of the new regulatory framework for banks, which goes beyond the micro-prudential capital requirements in two respects. First, under the current regulatory regime (Basel 3) banks have to hold capital buffers on top of micro-prudential minimum requirements, which can be drawn down in a crisis. These buffers consist of (*i*) a minimum 2.5 percent RWA capital conservation buffer, extended by (*ii*) a countercyclical buffer and by (*iii*) systemic buffers.[9] Second, banks have to hold sufficient long-term liabilities that can be transformed into capital through bail-in.[10] The Financial Stability Board has developed international standards for resolution frameworks, which have been implemented by most jurisdictions (FSB, 2014). These standards should reduce the need for public support measures as banks could orderly fail and their shareholders and creditors would bear the losses.

The historical losses presented in Section 3 provide a benchmark for total loss absorbing capacity needed to weather a systemic crisis. Three qualifications are in order, however:

- Requiring a (nearly) zero-failure level of loss absorbing capacity is particularly relevant for systemically important banks. Not all banks in our sample would qualify as such, although most of the *current* EU banks with total assets larger than EUR 30 bn – and all banks larger than EUR 150 bn – have been designated as systemically important institutions by their national authorities (Figure 5). Moreover, a significant proportion of banks in all size categories has

[9] There are three types of systemic buffers in the EU: a buffer for global systemically important institutions (the G-SII buffer), a buffer for other systemically important institutions (O-SII) and a systemic risk buffer (SRB) that may be imposed more generally for non-cyclical systemic risks. In this paper, we refer to the combination of these three components as "systemic buffer".

[10] More specifically, the Total Loss-Absorbing Capacity for G-SIBs (TLAC) is 18 percent of risk-weighted assets and 6.75 percent of total (unweighted) exposures. TLAC covers all capital and bail-in requirements except capital buffers, which must be met in addition to the TLAC RWA Minimum. Bail-in requirements for European banks (Minimum Requirements for Eligible Liabilities or MREL) have not yet been finalized.

received state aid to prevent failures (Table 1), which in many cases has been motivated by concerns about systemic risk.

- Losses are not a perfect measure of capital erosion because they are not corrected for regulatory adjustments, such as changes in goodwill and deferred tax assets. As such items are excluded from the definition of capital, losses that are written down from e.g. goodwill are less relevant from a regulatory perspective. Unfortunately, we do not have sufficient information on regulatory adjustments for most banks in our sample. We do not expect, however, that taking into account regulatory adjustments would have a material impact on our results.[11]
- Historical losses are not the only way to establish banks' required loss-absorbing capacity. Following the Basle Committee (BCBS, 2013), the most standard methodology to calculate bank-specific buffers is an expected impact approach, which calibrates systemic surcharges at a level that makes the expected impact of a systemic bank's failure equal to that of a non-systemic bank.[12] Our analysis of historical losses is not suited to draw conclusions about the required level of loss absorbing capacity of each *individual* bank in our sample, but can be used as a cross-check for the sample as a whole.[13,14]

To what extent are current systemic capital buffers – i.e. banks' first line of defense – sufficient to absorb losses of the order of magnitude we have seen in recent years? Figure 5 presents an overview of systemic buffers imposed on EU banks, as announced by national authorities to date.[15] For more than half of the banks, systemic buffers are at most 1 percent and in many cases smaller or even

[11] The Financial Stability Board's study on historical losses (FSB, 2015) presents losses with and without regulatory adjustments. Although both approaches lead to substantial differences for some individual banks, the overall results for the entire sample are very similar. Strah et al. (2013) present accumulated losses for US banks, taking into account regulatory adjustments.

[12] The BCBS (2013) analysis has set a 1-4.5 percent range for systemic surcharges. The Federal Reserve Board (2015) and the Bank of England (2016) use similar methodologies. Two alternative approaches that have been proposed are to calibrate capital buffers on the basis of an economic cost-benefit analysis or to set buffers at a level that would offset the funding cost advantage of a too-important-to fail bank (BCBS, 2013; FSB, 2015).

[13] The BCBS (2010) and the Bank of England (2016) also present historical losses next to, respectively, stress-test results and the expected-impact framework, as input for the calibration of capital buffers in general, rather than for individual banks. The FSB (2015) presents historical losses as one of its impact assessment studies underlying the TLAC calibration, but does not directly relate the losses to the TLAC ranges that have been set.

[14] Historical losses have been used as input to the expected impact approach, to establish the probability of default. BCBS (2013), Federal Reserve Board (2015) and Bank of England (2015) use the historical distribution of the return on risk-weighted assets (RORWA) to establish the share of banks with losses beyond a specific cut-off point, which is used as a proxy for the probability of default. This probability is combined with an indicator of damage (or loss-given-default), which are typically based on total assets or the Basle systemic important scores.

[15] Authorities typically announce such measures on their websites. See ESRB (2016) for an overview of systemic buffers imposed on EU banks.

zero. Such buffer requirements are modest compared to the losses banks experienced in the 2007-2016 period. With a systemic surcharge of 1 percent or less, the total buffer is likely to be in a range of 3-5 percent RWA, depending on the level of the countercyclical buffer. This would have been insufficient to cover the losses in about one third of the cases presented in Section 3. Using an expected impact framework, Passmore and Von Hafften (2017) draw a similar conclusion for G-SIB buffers. They conclude that buffer surcharges should be higher than the range set by the BCBS (2013) and be applied to a larger set of banks than the current G-SIBs.

[FIGURE 5 Systemic buffers EU banks, by size category]

If buffers are insufficient, banks would have to raise new capital or, if impossible given market conditions, go into insolvency or resolution. In a gone-concern situation, bail-in can be used to absorb losses and recapitalize a bank. This would require sufficient loss-absorbing capital, but also a clear commitment to apply bail-in if needed. A straightforward way to determine the amount of loss absorbing capacity needed is the sum of accumulated losses and minimum capital requirements (say, 10 percent RWA for pillar 1 and 2 combined) minus buffers (say, 5 percent) that can be drawn down. For the 10 percent worst cases in Figure 3, this would require loss absorption capacity – including buffers – of more than 25 percent RWA.

6 Conclusion

Initial assessments of the global financial crisis primarily focused on the vulnerability and systemic importance of large, market-oriented banks, which were hit most in the early phase of the crisis.[16] However, our results show that the relationship between bank characteristics and performance in a crisis is more ambiguous when the full post-2007 period is taken into account. Medium-sized and retail-oriented banks, which weathered the 2007-2009 crisis relatively well, turned out to be particularly vulnerable in the subsequent European debt crisis and even needed more state aid than the largest banks.

[16] See the references in Section 2. Moreover, the first initiatives to address too-importans-to-fail focused on what has become known as global systemically important banks (G-SIBs), which largely correspond to our subset of largest (> EUR 500 bn) banks. See, for instance, the initial list of G-SIBs published by the FSB (2011).

In line with the early empirical assessments of the crisis, regulatory requirements have been particularly tightened for global, systemically important banks, for instance by imposing systemic capital surcharges and bail-in requirements. While these measures remain essential to promote the financial system's resilience, the overall experience in Europe illustrates that prudential measures to mitigate systemic risk and too-important-to-fail incentives are just as relevant for broader categories of banks.

References

Altunbas, Yener, Simone Manganelli and David Marques-Ibanez, 2011, Bank risk during the financial crisis: do business models matter? ECB Working Paper Series, No. 1394, Frankfurt

Ayadi, Rym, and Willem Pieter de Groen (2014), Banking business models monitor 2014, CEPS, Brussels

Basel Committee on Banking Supervision (BCBS), 2010, Calibrating regulatory minimum capital requirements and capital buffers: a top-down approach, Basel

Basel Committee on Banking Supervision (BCBS), 2013, Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement, Basel

Bank of England (2016), The Financial Policy Committee's framework for the systemic risk buffer, London

Bekooij, Jack, Jon Frost, Remco van der Molen and Krzysztof Muzalewski (2016), Hazardous tango: Sovereign-bank interdependencies across countries and time, *DNB Working Paper*, No. 541.

Beltratti, Andrea, and René Stulz, 2012, The credit crisis around the globe: why did some banks perform better? *Journal of Financial Economics*, 105, pp. 1-17.

Board of Governors of the Federal Reserve System (FRB) (2015), Calibrating the GSIP surcharge, Washington DC

De Haan, Leo (2003), Microdata evidence on the bank lending channel in the Netherlands, *De Economist*, 151(3), pp. 293-315.

Demirgüç-Kunt, Asli, and Harry Huizinga (2010), Bank activity and funding strategies: The impact on risk and returns, *Journal of Financial Economics*, 98, pp. 626-650.

Detragiache, E., T. Tressel and R. Turk-Ariss (2018), Where have all the profits gone? European bank profitability over the financial cycle, *IMF Working Paper*, WP/18/99, Washington DC.

Drees, B., and C. Pazarbasioglu (1998), The Nordic Banking Crisis: Pitfalls in Financial Liberalization: Pitfalls in Financial Liberalization, *IMF Occasional Paper*, No. 161.

European Banking Authority (EBA) (2015), *Overview of the potential implications of regulatory measures for banks' business models*, London.

European Central Bank (ECB) (2016), *ECB Banking Supervision: SSM priorities 2017*, Frankfurt

European Systemic risk Board (ESRB), 2014, The ESRB Handbook on Operationalising Macro-prudential Policy in the Banking Sector, Frankfurt.

European Systemic risk Board (ESRB), 2016, *A review of Macroprudential Policy in the EU in 2015*, Frankfurt.

Financial Stability Board, 2011, *Policy measures to address systemically important financial institutions*, Basel.

Financial Stability Board, 2014, *Key attributes of effective resolution regimes for financial institutions*, Basel.

Financial Stability Board, 2015, *Historical losses and recapitalisation needs*, Basel.

Financial Stability Board, 2017, *Implementation and effects of the G20 financial regulatory reforms*, Basel.

Houben, A., *New instruments for a resilient financial system*, Inaugural lecture, University of Amsterdam.

Independent Commission on Banking (2011), *Final report: recommendations*, London.

Klomp, J., and J. de Haan (2012), Banking risk and regulation: does one size fit all?, *Journal of Banking and Finance*, 36, pp. 3197-3212.

Laeven, Luc, Lev Ratnovski and Hui Tong, 2014, Bank size and systemic risk, *IMF Staff Discussion Note*, SDN/14/04, Washington DC.

Liikanen (2012) (chair), High-level Expert Group on reforming the structure of the EU banking sector, Brussels.

Lucas, André, Julia Schaumberg and Bernd Schwaab (2016), Bank business models at zero interest rates, Tinbergen Institute Discussion Paper, TI 2016-066/IV

Mulaik, S.A. (1972), *The Foundations of Factor Analysis*, McGraw-Hill, New York.

Passmore, W., and A.H. von Hafften (2017), Are Basel's capital surcharges for global systemically important banks too small?

Poghosyan, T., C. Werger and J. de Haan (2016), Size and support ratings of US banks, *North American Journal of Economics and Finance*, 37, pp. 236-247.

Pouw, L., and J. Kakes (2013), What drives bank earnings? Evidence for 28 banking sectors, *Applied Economics Letters*, 20(11), pp. 1062-1066.

Shehzad, C.T., J. de Haan and B. Scholtens (2010), The impact of bank ownership on impaired loans and capital adequacy, *Journal of Banking and Finance*, 34, pp. 399-408.

Strah, S., J. Hynes and S. Shaffer (2013), The impact of the recent financial crisis on the capital positions of large US financial institutions: an empirical analysis, Federal Reserve Bank of Boston,

Van Ewijk, Saskia, and Ivo Arnold (2014), How bank business models drive interest margins: evidence from US bank-level data, *European Journal of Finance*, pp. 850-873.

ANNEX A Data and definitions

A.1 Sample of banks

Our total sample includes 282 banks from the European Union (EU), with a core set of 116 banks that have total assets higher than EUR 30 bn in the first year of the peak accumulated losses interval. Only banks at the group level are included, i.e. subsidiaries – also from non-EU banks – are excluded. There have been several mergers and acquisitions. In principle, a bank that has been taken over is included in our sample up to the point where it was acquired. Our approach avoids double-counting, which allows us to aggregate losses in each year. Because of data limitations, the analysis of business models in Section 4 is based on a subset of 69 banks. The loss patterns of this subset are representative for of the entire sample, however (Figure A2).

Data are taken from the SNL Financial database, which covers most of the EU banking system. Aggregate assets of our sample were on average around EUR 32 trn, which represents the bulk of the ECB's consolidated banking data for domestic consolidated banks (on average about EUR 35 trn over the years 2008-2016). Besides differences in consolidation, this difference may be attributed to the fact that we exclude bad bank constructions, while some banks are missing in the SNL database.

A.2 Definition of income

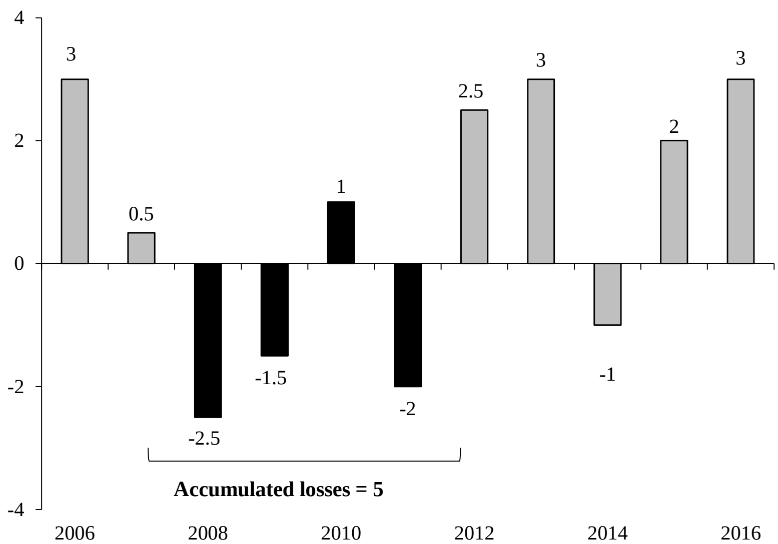
We use total comprehensive income (TCI), a broad definition of income which also includes unrealized losses that are not directly reflected in the profit and loss statement. A further refinement would be to correct TCI for regulatory adjustments, such as goodwill and deferred tax assets, to arrive at a measure of (core) tier 1 capital erosion. The FSB study on banks' historical losses (FSB, 2015) shows that the impact of regulatory adjustments can be substantial for individual banks but does not lead to a different overall picture of losses across banks.[17] We also calculated losses based on net income, i.e. only insofar as reflected in the profit and loss statement. This narrower measure leads to about 20 percent lower losses over the entire period. Most of this difference with TCI is concentrated at large banks in the year 2008, which further increases the performance gap between medium-sized and large banks.

[17] Strah et al. (2013) also present historical losses of US banks with a correction for regulatory adjustments, in order to calculate the impact on regulatory capital.

A.3 Definition of peak accumulated losses

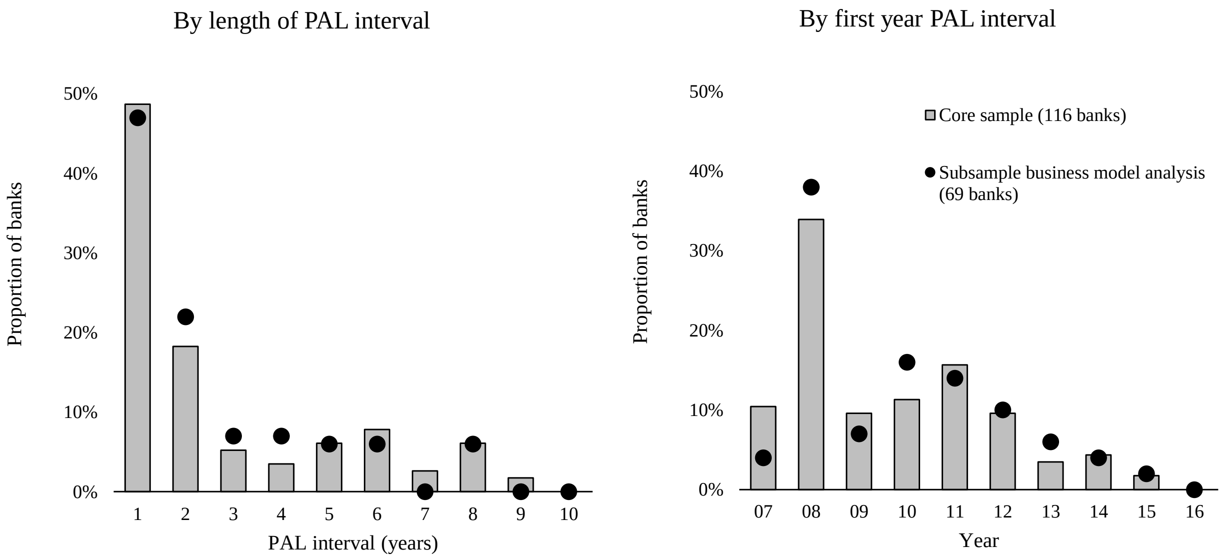
Following other studies, this paper uses peak accumulated losses (PAL) as a main indicator. This measure aggregates income over an interval that maximizes losses during the 2007-2016 period. The interval may include one or more years of positive income, as illustrated in Figure A1. For banks that did not experience negative income in any year, this metric is simply the lowest positive income. Losses are expressed in terms of total and risk-weighted assets in the first year of the loss interval. An alternative would be to use average assets over the total loss interval, which leads to somewhat higher loss ratios because many banks have become smaller.[18] The use of annual instead of quarterly data also contributes to lower loss ratios, as losses in a particular quarter may be compensated with positive net income in another quarter. For most banks, the PAL interval is 1 or 2 years and starts in 2008 or around 2011, consistent with the two waves of losses during our sample period.

Figure A1 Stylized illustration peak accumulated loss



[18] Using average assets instead of initial assets leads on average to about 0.5 percentage points higher loss ratios for medium-sized and large banks.

Figure A2 Distribution of banks by length and start of PAL interval
Banks with total assets > EUR 30 bn, proportion of banks by sample

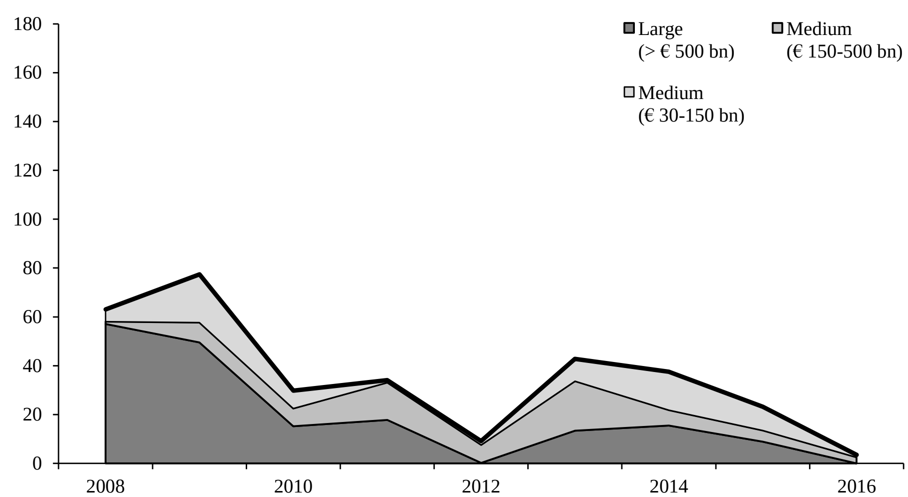


Source: SNL, own calculations

A.4 Share issues and state aid

Share issues are taken from the SNL database, for all EU banks with total assets higher than EUR 30 bn in at least one year in our sample. Not all share issues are used to repair balance sheets; they can also be used for funding to finance acquisitions or to repay state aid. About two thirds of the share issues we considered, however, have been motivated by the aim to strengthen balance sheets. Moreover, aggregate issues follow the same pattern as aggregate losses, with two waves around 2009 and 2013 (Figure A3).

Figure A3 Share issues by EU banks
Share issues (EUR bn)

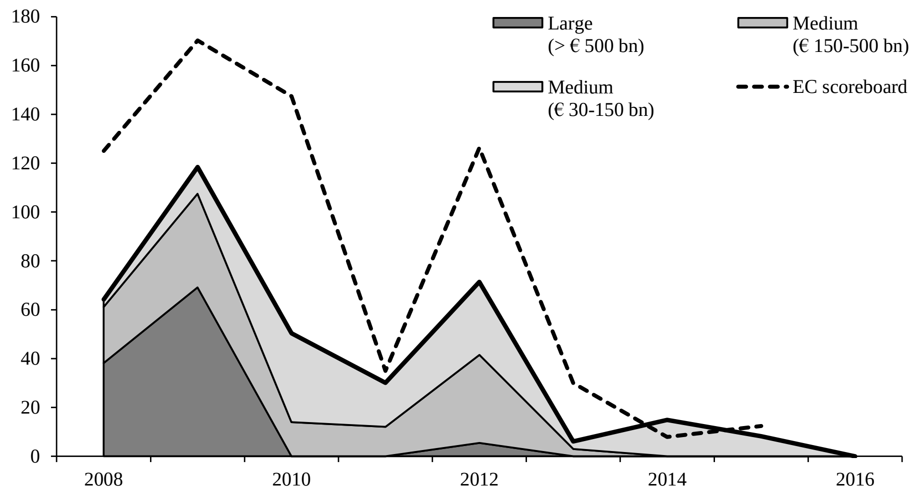


Source: SNL, own calculations

State aid is based on the European Commission's assessments that are published in its state aid register. We only included direct capital injections and impaired assets measures (primarily asset purchases and guarantees by governments), insofar as the latter have been expressed in terms of an equivalent of direct capital support. For example, the Dutch State's back-up facility for ING, which involved a transfer of part of ING's risks on its USD 39 bn Alt-A mortgage portfolio, was assessed to be equivalent to an amount of EUR 5 bn state aid. We did not include cases where the amount of aid has not been quantified this way. In addition, we only considered state aid for our core set of banks with total assets higher than EUR 30 bn. Hence, the aggregate amount of aid used in our analysis is lower than the total amount reported by the European Commission in its State Aid Scoreboard, although it follows the same pattern (Figure A4). In line with the development of losses, initially most state aid was given to the largest banks, but in subsequent years medium-sized banks received the bulk of state aid.

Figure A4 State aid to EU banks

Capital injections and impaired asset facilities *EUR bn)



Source: European Commission, FSB (2015), own calculations

Banks benefited from public sector support in more ways than through the state aid presented here. Governments also provided significant funding support, mostly by guarantees on new funding. In addition, central bank funding was facilitated by increasing the maturity of refinancing operations. Finally, banks benefited indirectly from public sector support their their counterparties. Obviously, it is difficult if not impossible to quantify these additional support measures, so we did not take them into account.

ANNEX B Identification of bank business models using factor analysis

To limit the number of variables characterizing banks, we apply factor analysis. Factor analysis aims at finding a 'common factor', x_k, which is an unobservable, hypothetical variable that contributes to the variance of several (at least two) observed variables, y_j. The equation of the common factor model is (Mulaik, 1972):

$$y_{ij} = \sum_{k=1}^{q} x_{kj}\, b_{kj} \qquad \text{(B1)}$$

where i denotes the observation. There are q common factors in this equation, which are conveniently assumed to be uncorrelated with each other. b_{kj} is the regression coefficient for predicting observed variable j using the k^{th} common factor. e_{ij} are residuals that are uncorrelated both with each other and with the common factors. In matrix notation it reads:

$$Y = XB + E \qquad \text{(B2)}$$

B is the factor pattern, which lends itself to interpretation of the meanings of the common factors, as will become clear below.

From a larger set of variables, we selected 15 variables that are available for a significant number of banks in our sample and for most of the sample period. The goal of factor analysis is to cluster variables into factors on the basis of correlations among variables and factors. Variables that are strongly correlated are transformed into a first factor, under the condition that this factor is not orthogonal to the second factor, and so on. To improve the interpretation of the factor loadings that are obtained from the analysis, an orthogonal rotation is performed to obtain a simple structure so that the rotated factors become uncorrelated. This standard procedure in factor analysis reduces the problem of having too many variables loading on one factor or a variable showing significant loading on more than one factor. An analysis of the 'eigenvalues' of the factors, and several significance tests help to decide on how many factors to retain.

Consequently, applying factor analysis on our 15 variables, we obtain two 'common factors' contributing substantially to the variance of these 15 variables[19] and having economically interpretable and significant factor loadings. The first factor has large positive loadings on size, securities, derivatives, assets for trading and market risk (Table B1). Therefore, we label Factor 1 'Big investment banks'. The second factor has large negative loadings on income from fees and from trading, large positive loadings on interest income and liquid assets. Hence, we label Factor 2 'Retail banks'. The conclusion from this factor analysis is that two types of banks can be distinguished: big investment banks and retail banks.

We use this distinction when examining differences in peak losses between bank business models. Therefore, we use dummy variables for each of two factor variables, Factor 1 and Factor 2, respectively, which are either 1 or 0.

[19] The shape of a plot of the factors' eigenvalues indicates that the marginal contributions of the first two factors are the greatest.

Table B1 Factors and factor loadings

Variable	Factor 1 'Big investment banks'	Factor 2 'Retail banks'
Size: log(total assets)	**0.699**	-0.010
Net interest income	-0.161	**0.763**
Fees & commissions	0.345	**-0.485**
Trade income	-0.003	**-0.665**
Cash & cash equivalents	0.227	**0.833**
Securities	**0.867**	0.239
Bank deposits	-0.120	0.067
Net loans to banks	0.224	**0.854**
Total net loans	**-0.729**	**-0.569**
Derivatives held for trading	**0.920**	0.019
Assets held for trading	**0.935**	0.023
Risk mix	**0.654**	-0.094
Equity ratio	-0.270	-0.306
Tier1 ratio	0.183	0.144
Loan to deposit ratio	-0.207	-0.435
Eigenvalue	4.851	2.858
Cumulative proportion of variance explained	0.439	0.697

Factor loadings have been rotated using orthogonal Varimax. Factor loadings absolute values equal to or higher than 0.4 have been printed in bold.

TABLES MAIN TEXT

Table 1 Characteristics different size classes EU banks

	Total	Size categories				GIIPS
		Small	Medium		Large	
		< 30	30-150	150-500	> 500	
Number of banks	282	166	68	27	21	97
Aggregate (EUR bn)						
Total assets[a]	38.114	1.563	4.634	7.483	24.434	8.219
Aggregated losses	648	37	177	134	300	298
Peak accumulated losses[b]	574	34	162	122	257	270
Equity issues[c]	332	-	73	77	182	146
State aid[d]	369	-	124	132	113	174
Proportion of state aid cases [e]	*40%*	-	*43%*	*41%*	*29%*	*53%*
Averages (%) [f]						
Peak acc. losses/TA	2.5%	2.4%	3.5%	1.7%	1.2%	4.4%
Peak acc. losses/RWA	4.4%	4.0%	6.0%	3.7%	3.4%	6.9%
RWA density (RWA/TA)	56.2%	64.1%	52.5%	39.7%	35.4%	63.8%
Credit gap home country[g]	13.2%	14.0%	16.7%	8.5%	3.6%	29.5%

[a] Aggregated bank assets at the end of the initial year of banks' peak accumulated loss interval.
[b] Peak accumulated losses in the 2007-2016 period, calculated for each bank, aggregated by subset.
[c] Total volume of share issues in the 2007-2016 period, aggregated by subset.
[d] Aggregated capital support, state aid assessments by the European Commission, as of end-2017.
[e] Only core set of banks with total assets > EUR 30 bn.
[f] Simple averages across (sub)samples.
[g] Deviation of credit-to-GDP ratio from its long-term trend, based on end-2007 data and calculated following the methodology developed by the Basel Committee (BCBS, 2010b).

Source: SNL, ECB, European Commission, own calculations

Table 2 Regression results. Dependent variable: peak accumulated loss

A. Regression results

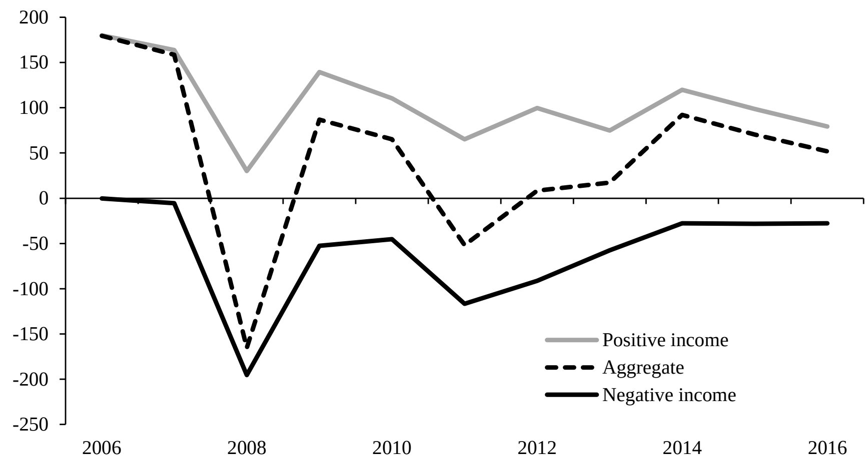
	By Factor	By Factor & Period	By Factor & GIIPS
	Eq. (1)	Eq. (2)	Eq. (3)
Factor1	0.98***	2.08***	0.06
Factor2	0.16	0.28	-0.03
Factor1 × Period1		-1.88**	
Factor2 × Period1		-0.60	
Factor1 × GIIPS			1.47
Factor2 × GIIPS			-6.24**
Period1 × GIIPS			
Factor1 × Period1 × GIIPS			
Factor2 × Period1 × GIIPS			
Period1		-1.55**	
GIIPS			-4.47***
Constant	-2.46***	-2.92***	-1.03***
Number of observations	69	69	69
F-value	4.47***	2.59**	3.60***
R^2	0.07	0.18	0.38

B. Marginal effects

	Eq. (1)	Eq. (2)	Eq. (3)
Factor1	0.98***		
Factor2	0.16		
Factor1, Period1		0.20	
Factor1, Period2		2.08***	
Factor2, Period1		-0.33	
Factor2, Period2		0.28	
Factor1, non-GIIPS			0.06
Factor1, GIIPS			1.54
Factor2, non-GIIPS			-0.03
Factor2, GIIPS			-6.27**

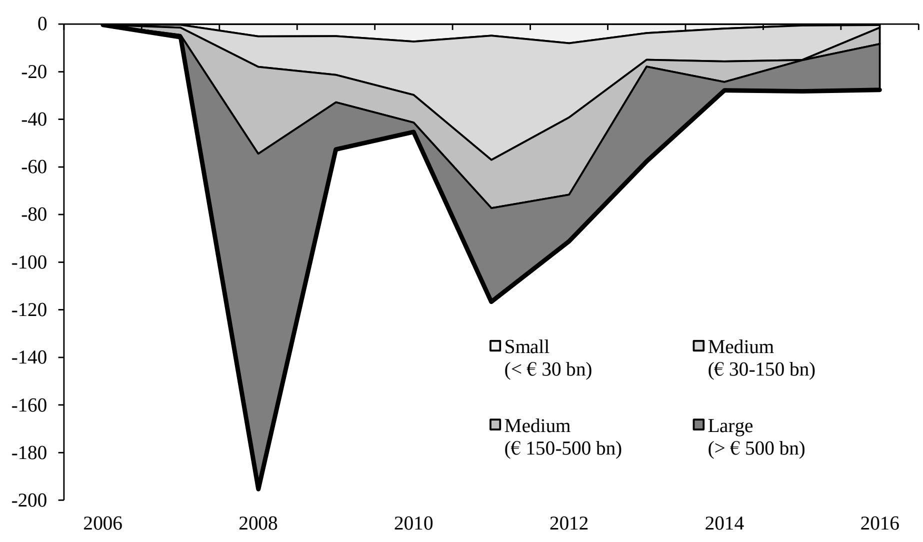
FIGURES MAIN TEXT

Figure 1 Bank earnings 2006-2016: a double dip
Total comprehensive income; aggregate for 280 EU banks.



Source: SNL, own calculations

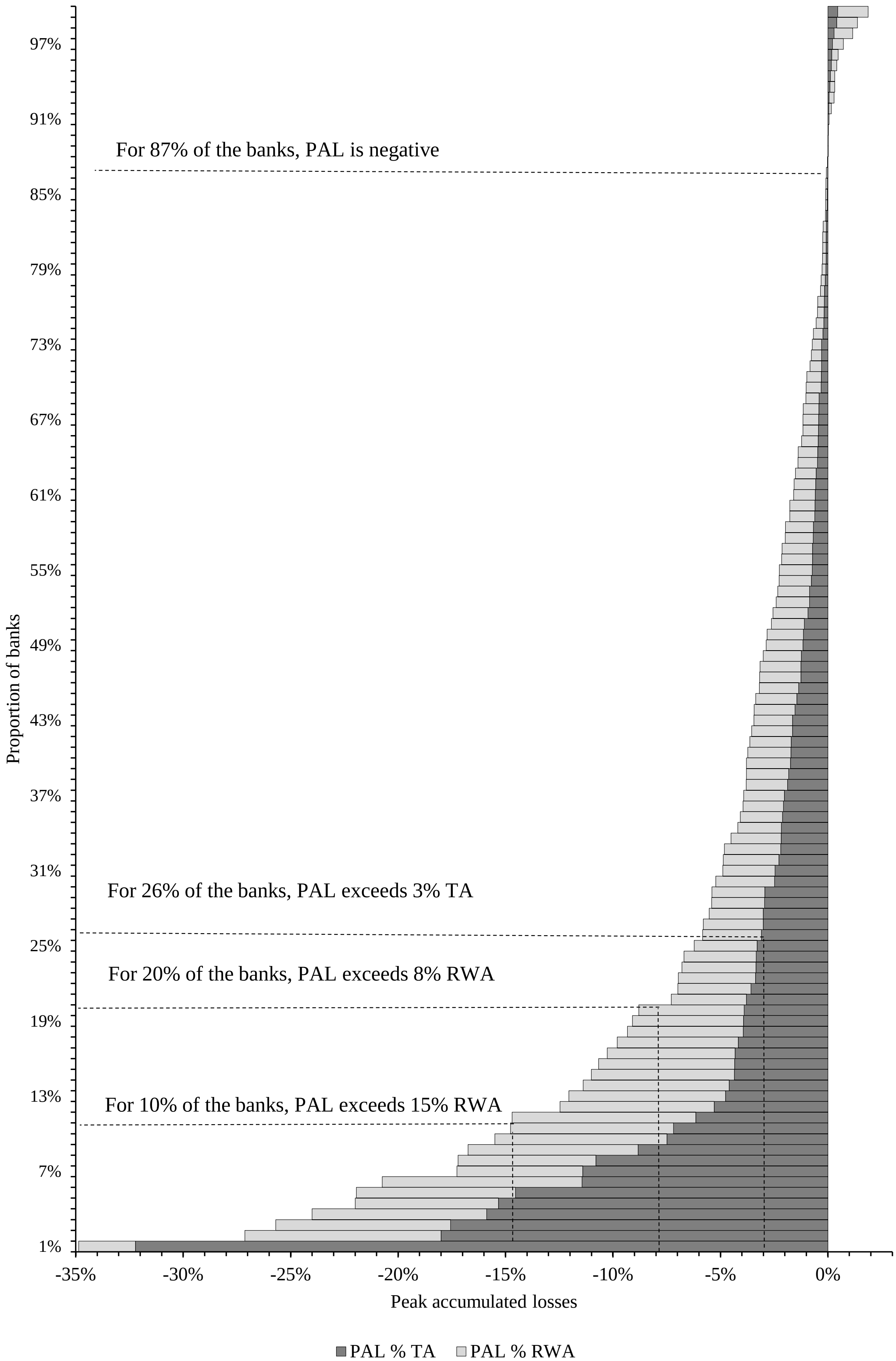
Figure 2 Largest banks hit first, smaller banks later
Aggregated annual losses (EUR bn) by size class (total assets). Same population as Figure 1.



Source: SNL, own calculations

Figure 3 Distribution peak accumulated losses across banks

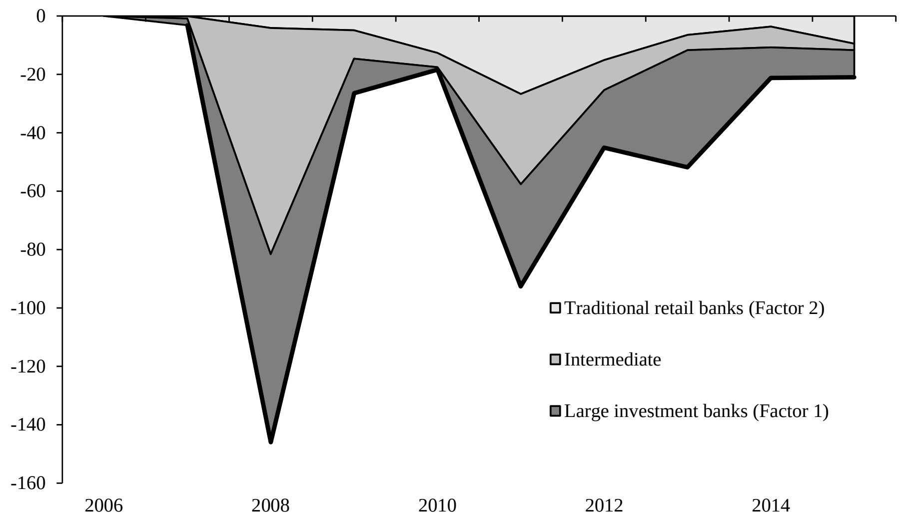
Peak accumulated losses % (risk-weighted) assets for 116 EU banks (total assets > EUR 30 bn).



Source: SNL, own calculations

Figure 4 Losses by business model category

Aggregated annual losses (EUR bn) for subset of 69 banks included in the business model analysis.

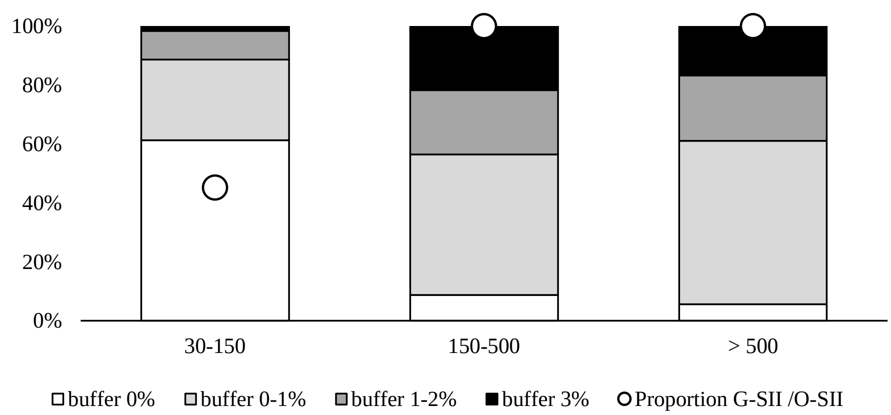


Banks are classified according to the difference between their Factor 1 and Factor 2 scores. For large investment banks, (Factor 1 – Factor 2) > the sample's third quartile of (Factor 1 – Factor 2). For retail banks, (Factor 1 – Factor 2) < the sample's first quartile of (Factor 1 – Factor 2). For indeterminate or hybrid banks, (Factor1 – Factor 2) lies betweeen the first and third quartiles, i.e. within the interquartile range.

Source: SNL, own calculations

Figure 5 Systemic buffers EU banks, by size category

Proportion of banks with zero, 0-1, 1-2, or 3 percent systemic buffers



Total systemic buffer requirements (G-SII, O-SII and SRB) when fully phased in, as announced to date. Size categories according to the ECB classification of significant banks; non-SSM banks on the basis of end-2016 assets. Banks (103 institutions) are only included at the group level, i.e. subsidiaries are excluded. "Proportion G-SII and O-SII" is the share of by category banks that have been designated as G-SIIs or O-SIIs by national authorities.

Source: ECB, ESRB, national authorities

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