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EURO AREA POLICIES

FINANCIAL SECTOR ASSESSMENT PROGRAM

July 2018

TECHNICAL NOTE—SYSTEMIC RISK ANALYSIS

This Technical Note on Systemic Risk Analysis for the euro area was prepared by a staff team of the International Monetary Fund. It is based on the information available at the time it was completed in June 2018.

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June 29, 2018

TECHNICAL NOTE

SYSTEMIC RISK ANALYSIS

Prepared By
Monetary and Capital Markets Department

This Technical Note was prepared by in the context of the Financial Sector Assessment Program for the euro area led by Daniel Hardy. It contains technical analysis and detailed information underpinning the FSAP's findings and recommendations. Further information on the FSAP can be found at http://www.imf.org/external/np/fsap/fssa.aspx

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Glossary

AE	Advanced economies
CCA	Contingent claims analysis
EA	Euro area
EM	Emerging markets
FCI	Financial Conditions Index
FSB	Financial Stability Board
FVC	Financial vehicle corporation
FVCDS	Fair value CDS
GMM	General method moments
G-SIB	Global Systemically Important Bank
LCR	Liquid coverage ratio
MMF	Money market funds
NBNI	Nonbank non-insurance
NPL	Nonperforming loan
OFI	Other financial institution
PD	Probability of defaults
PDF	Probability density function
ROA	Return on assets
ROE	Return on equity
SI	Significant institutions
SSM	Single Supervisory Mechanism

EXECUTIVE SUMMARY

This technical note consists of five chapters focusing on various aspects of systemic risk analysis across the euro area financial system. The chapters cover bank profitability, balance sheet- and market-based interconnected analysis, contingent claims analysis, and a brief discussion of data gaps in the nonbank, non-insurance (NBNI) financial sector.

The ongoing economic recovery will support euro area bank profitability in general, but it is unlikely to resolve the structural challenges faced by the least profitable banks despite some recent improvements. This is important because persistently weak bank profitability is a systemic financial stability concern. Empirical analysis of 109 major euro area banks over 2007–2016 reveals that real GDP growth and the NPL ratio are the most reliable determinants of profitability, after accounting for other factors. Although higher growth would raise profits, a large swath of banks with the weakest profitability would most likely continue to struggle even with a robust recovery. Therefore, banks should take advantage of the current upswing by resolutely addressing their NPL stocks—such a strategy holds the most promise for weak banks' profitability prospects.

The analysis of financial system interconnectedness and spillovers takes both cross-sectoral and cross-country perspectives, centered on the major euro area banks:

- ***The appraisal of contagion risks using granular supervisory data suggests that the risk of contagion through interbank exposures within the euro area are currently low relative to extra-euro area exposures.*** Large SIs displays a modest degree of interbank connectedness relative to banks' capitalization levels. In contrast, a network depiction indicates that cross-border linkages, including with other European and U.S. banks, are relatively stronger. Country-level analysis corroborates these findings and indicates that euro area spillovers have been decreasing in recent years, in parallel with the downward trend in exposures with other banks.

- ***The results using equity prices suggest that stronger bank fundamentals reduce net spillovers from the rest of the world not only on average, but also in terms of tail risks*.** Lower NPL ratios, greater profitability, and higher capitalization levels are shown to decrease the probability of inward spillovers to the euro area banking system from the rest of the world. These effects appear to have strengthened in recent years. Furthermore, evidence suggests that progressively stronger fundamentals can increase the euro area banking system's resilience to inward spillovers without necessarily aggravating outward spillovers.

Contingent claims analysis, which uses market-based data encompassing banks, insurers, sovereigns, and the nonfinancial corporate sector, broadly corroborates the balance sheet-based solvency stress tests.

Data gaps in the nonbank, non-insurance (NBNI) segment of the financial sector may hinder comprehensive monitoring and appraisal of risks. Major strides have been made, but a sizeable gap remains which needs to be closed expeditiously.

DETERMINANTS OF EURO AREA BANK PROFITABILITY[1]

A. Introduction

1. **Despite the cyclical recovery, low profitability remains a challenge for many banks across the euro area.** Several banking system soundness indicators been improving on average. For example, across the largest euro area banks, capitalization and liquidity coverage ratios have generally risen. Two key headline profitability measures, return on assets (ROA) and return on equity (ROE), have also increased in 2017.[2] However, despite these improvements, low bank profitability remains a concern for numerous banks across the area. Both ROA and ROE have declined substantially after the global financial crisis and have remained at low levels for almost a decade (Figure 1). Moreover, forecasts by market analysts suggest that many banks' ROE levels will most likely remain below 8 percent even in 2019.[3]

2. **Persistently weak profitability is a systemic financial stability concern.** Bank capital serves as a cushion against an individual shock. Therefore, the inability of banks to (re-) build capital buffers by retaining earnings undermines their resilience. In addition, weaker profitability could foster undue risk taking to generate higher returns (gambling for resurrection), which would heighten systemic risk.[4]

3. **There is an active debate in both policy circles and academia on the relative importance of the main drivers of bank profitability.** Most papers acknowledge that profitability is driven by a combination of bank-specific, cyclical, and structural factors, albeit to varying degrees (see, for example, Demirguc-Kunt and Huizinga, 2010; Jobst and Weber, 2016; and Das and Xu, forthcoming). One side of the debate argues that cyclical factors, including growth, are relatively more important (see Kok, More, and Pancaro, 2015; and ECB, 2015, for European banks; and Albertazzi and Gambacorta, 2009, for a broader set of countries). The other side of the debate acknowledges the role of cyclical support, but highlights the importance of structural factors (see,

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[1] This chapter was prepared by Selim Elekdag, Sheheryar Malik (both Monetary and Capital Markets Department, IMF), and Srobona Mitra (European Department, IMF).

[2] The largest euro area banks (significant institutions, "SIs"), which are under the direct supervisory purview of the Single Supervisory Mechanism (SSM), registered a CET1 ratio of 14.6 percent in 2017Q4, and a Liquidity Coverage Ratio (LCR) above 100 percent on average. At the same time, profitability improved over the course of 2017. Notably, ROA and ROE for all SIs have risen to 0.41 percent and 5.98 percent in 2017 from 0.21 percent and 3.29 percent in 2016, respectively. See, for example, ECB Financial Stability Review (May 2018), Constâncio (2017) https://www.ecb.europa.eu/press/key/date/2017/html/ecb.sp171109.en.html, or https://www.bankingsupervision.europa.eu/banking/statistics/html/index.en.html

[3] The 8 percent ROE threshold is based on investor surveys suggesting that banks' cost of equity—with all the standard caveats about its measurement—is about 8–10 percent (GFSR 2017).

[4] Moreover, low profitability may inhibit proactively addressing impaired assets as write-down could further erode earnings. Weak banks profits could also potentially force banks to reduce assets and thereby hamper credit intermediation to the real economy. On gambling for resurrection and risk-shifting behavior, see GFSR, October 2014, Chapter 3.

for example, GFSR April 2017).[5] Comparing profitability of European banks to global peers, Detragiache and others (2018) shows that banks loan quality and cost efficiency were the major determinants of changes to their profitability.

4. Much of the literature focuses on average profitability dynamics across banks or on relative efficiency. These papers report how selected determinants affect bank profitability in average terms (based on point estimates). Although this is standard practice, it could potentially misinform policymakers, especially when considering a very heterogeneous banking system such as that in the euro area. For instance, the profitability of the average bank would likely increase amid an upswing, but this may reflect that the beneficial effects of greater growth accrue disproportionately to stronger banks. Therefore, only focusing on the soundness of banks on average could result in possibly misleading conclusions, especially when deeper structural problems are concentrated in the weaker tails of the bank profitability distribution.

5. This study attempts to fill these gaps by addressing the following questions: What are the key bank-specific, cyclical, and structural determinants of bank profitability? How would a change in these determinants affect the conditional distribution of banks' profitability? More specifically, how would higher growth, or for example, a lower nonperforming loan (NPL) ratio, affect the profitability distribution, particularly the lower tail of the distribution?[6]

6. Focusing on large euro area banks, this chapter addresses these questions with relatively novel approaches:

- First, to lay the ground work and facilitate comparability with the literature, panel regression analysis is used to establish the most reliable determinants of bank profitability. The analysis focuses on the profitability of the largest euro area banks ("significant institutions," or SIs) which are under the supervisory perimeter of the Single Supervisory Mechanism (SSM) over 2007–2016.

- Second, in the more novel part of the chapter, quantile regressions are used to generate profitability distributions conditional on bank-specific, cyclical, and structural determinants. Selected determinants are then shocked to assess how the shape of the profitability distribution for a "representative" bank changes—an approach which clearly goes beyond standard comparative statics centered on averages. Importantly, this powerful method can be used to quantify how selected determinants influence the probability of banks' profitability being above or below a certain threshold deemed important for market analysts or policymakers.

[5] Other studies emphasize other cyclical determinants of bank profitability including financial and monetary conditions (Detragiache, Tressel, and Turk-Ariss, 2018; Borio, Gambacorta, Hofmann, 2017).

[6] Quantification of the lower tail allows gauging the extent of potential downward drag on profitability (of the representative bank).

7. The main results of the chapter can be summarized as follows:

- The most robust determinants of bank profitability across large euro area banks appears to be real GDP growth and the NPL ratio after accounting for other factors. Higher growth by the order of 1 percentage point is associated with a 15–35 basis point rise in ROA, which is considerable given that average ROA over 2007–2016 was 34 basis points.[7] At the same time, recall that growth over the sample period had an average of 0.8 percent—in other words, the increase in growth by a percentage point is large. A 1 percentage point decline in the NPL ratio can lift ROA by about 4–9 basis points.[8]

- Although higher growth would lift profitability on average, it may not affect all banks to the same degree. This is evidenced by illustrative conditional profitability distributions estimated for the 109 SIs in the sample over 2007–2016. Estimates suggest that the likelihood of a (representative) bank's ROE falling below 8 percent remains elevated at 63 percent. A hypothetical scenario indicates that greater growth, by 1 standard deviation, reduces this likelihood by about 14 percentage points. Note that the standard deviation of growth is high at 3.3 percent.

- However, under a scenario with higher growth and lower NPLs, the probability of a representative bank with ROE less than 8 percent now declines to approximately 50 percent (and the likelihood of a bank with negative profitability is about 25 percent). This scenario could be interpreted as an aggressive NPL reduction in the context of a robust economic upswing.

- As for other results, the study finds that lower cost-to-income ratios are associated with higher profitability for banks outside of the weakest end of the profitability spectrum, but that the results on business models and market concentration are more mixed. In addition, higher short-term interest rates and a steeper yield curve generally do not appear to raise ROA or ROE.

8. A key takeaway is that the current recovery alone will likely be insufficient to resolve many banks' profitability challenges:

- Notwithstanding the positive association between growth and bank earnings, the needed cyclical upswing is very large and will most likely not be durable. Recall that euro area potential growth is estimated to be about 1½ percent, putting into sharp relief the plausibility of a sustained 1 percentage point increase in economic activity.

- Given that the combination of higher growth and lower NPLs reduces the probability of negative profitability the most, the current economic expansion presents a window of opportunity to reduce NPLs in a more determined manner.

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[7] Note that ROA increased from 0.21 percent in 2016 to 0.41 percent in 2017 on average across all SSM banks: https://www.bankingsupervision.europa.eu/banking/statistics/html/index.en.html

[8] The NPL ratio declined from 6.15 percent in 2016 to 4.92 percent in 2017 for all SIs on average: https://www.bankingsupervision.europa.eu/banking/statistics/html/index.en.html

- At the same time, a more targeted strategy is needed to adjust business models and address cost efficiencies. Since weak profitability is pervasive across many business models, factoring in bank-specific circumstances are especially important in the context of more longer-term viability. Although cost reductions help raise profitability, this relationship is stronger for the more profitable banks, which emphasizes the importance of prioritizing NPL reductions for many of the weakest banks. Opportunities arising from FinTech should be wholeheartedly embraced, including through digitalization.

- In sum, banks should take advantage of the robust cyclical recovery to resolutely address their profitability challenges from multiple angles including decisive NPL reduction, efficiency enhancements, and a tailored approached to revamping business models.

B. Conceptual and Empirical Framework

This section begins with a brief review of the literature on the determinants of bank profitability, then provides an overview of the econometric framework. It then discusses the most novel aspect of the study: the generation of bank profitability distributions conditional on selected determinants.

Conceptual Framework

9. The theoretical and empirical literature has proposed several determinants of bank profitability, which can be grouped into three broad categories: (1) bank-specific, (2) cyclical, and (3) structural. Key determinants, the rationale for their inclusions, and previous empirical results on their relevance are summarized below. In many cases, the theoretical impact of these determinants on profitability remains inconclusive, which further motivates the empirical investigation.

Bank-specific Determinants

10. Broadly speaking, bank-specific determinants of profitability can be split into two categories. The first encompasses financial soundness indicators such as solvency and asset quality, while the second category is broader and covers measures of size, efficiency, diversification, and business models. The set of bank-specific determinants are generally similar across many empirical studies (selected examples include Demirguc-Kunt and Huizinga, 2010; Kok, More, and Pancaro, 2015; ECB, 2015; and Borio and others, 2017).

- ***Solvency***: Although bank capital is considered an important determinant of profitability, its impact is ambiguous. Banks with higher capitalization ratios tend to face lower funding costs owing to lower bankruptcy costs thus supporting earnings (Berger, 1995). In contrast, greater capital ratios may be associated with lower risk-taking and thereby lower expected returns (Goddard and others, 2004). Likewise, as banks get closer to default (when capital is nearly depleted), shareholders and managers have less to lose from failure (and more to gain from success), and so may be willing to take excessive risks (and "gamble for resurrection") with the hope that greater earning will restore solvency (GFSR 2014, October, Chapter 3).[9]

- ***Asset quality*: ** NPLs—a standard measure of asset quality—are used as a risk management metric, and the level of risk is a key factor driving banks' overall performance. Greater risk and returns tend to go hand in hand, at least in the near term. However, banks which take on greater risks tend to eventually incur higher losses which reduce returns. Empirical evidence suggests that higher credit risk (proxied with NPL or provisioning ratios) is characterized by lower profitability (Bikker and Hu, 2002).

- ***Size*:** Controlling for bank size is important, but its relation to profitability is not conclusive. Some studies argue that larger banks benefit from economies of scale thereby enhancing the bottom line (Shehzad and others, 2013). In contrast, other studies claim that larger banks suffer from diseconomies to scale reflecting agency, overhead, and managerial costs (Tregenna, 2009).

- ***Efficiency*:** Better operating efficiency is typically associated with greater bank profitability (Molyneux and Thornton, 1992). Standard measures include cost-to-income or cost-to-assets ratios, occasionally differentiating between personnel and non-personnel costs (Demirguc-Kunt and Huizinga, 2010).

- ***Diversification*:** The link between more diverse revenue streams and profitability is also contested. Some studies claim that there is a positive relationship (Valverde and Fernandez, 2007), but perhaps to a certain degree (Gambacorta and others, 2014), while others find a negative link as a higher share of non-interest income is associated with more volatile earnings (Stiroh, 2004).

- ***Business models*:** It is also important to consider banks' diverse business models. While several studies have proposed business model classifications, such characterizations have overlapping features that are sometimes difficult to correlate with profitability (Ayadi and others, 2015; BIS, 2017; GFSR 2017). Therefore, as a first pass, the deposit-to-asset and loan-to-asset ratios are used as two broad indicators of balance sheet characteristics of banks that describe the thrust of their business models.[10]

Cyclical Determinants

11. Accounting for the macroeconomic environment is standard practice, and many studies find that profitability is procyclical. An economic expansion will increase the demand for intermediation services (including lending and underwriting and advisory services) thereby lifting

[9] Such a hypothetical situation is likely to be associated with insufficient governance and risk management frameworks. Likewise, risk-taking behavior is likely to be influenced by the macroeconomic environment, whereby banks' risk tolerance may increase or lending standards may decrease during booms for example.

[10] Both in the context of revenue diversification and as a business model indicator, the trading assets-to-total assets ratio was considered, but not included because of a dearth of data.

both net interest income, fees, and commissions. In addition, improving asset quality with reduce the need for loan loss provisioning which also contributes to profitability.[11]

12. Other cyclical factors—such as financial conditions—can also influence banks' profitability. Many of the aforementioned studies control for inflation, policy rates and the slope of the yield curve. More generally, Detragiache and others (2018) investigate profitability over the financial cycle. It will also be important to account for major crisis periods to ensure such shocks are not driving the results. In the baseline and most other specification, time fixed effects are included to capture regional and global developments that may affect profitability. In the robustness analysis, a new euro area financial conditions index (FCI) was used which includes measures of spreads and volatility which tend to spike during turbulent market conditions (for details, see Arregui and others, 2018). Another benefit of including FCIs is that they include real estate prices which may be particularly important given the role of real estate as collateral. Country-specific versions of the FCI were used. In addition, an aggregate euro area FCI was considered (but not shown for brevity), and crisis dummies were included for selected euro area countries.

Structural and Other Determinants

13. Market concentration is one of most commonly used structural determinants of bank profitability. Opposing hypotheses consider whether concentration results in collusion or greater competition with attendant implications on bank revenues.[12] Other determinants including ownership, governance, and supervisory regimes could also affects banks performance, however, because of data limitations, they are not considered in this study.[13]

Econometric Approach

14. To set the stage, and to facilitate comparability with other studies, the empirical approach begins with standard panel regression analysis. An abridged representation of the baseline specification is as follows:

$$y_{b,c,t} = \alpha * X_{b,c,t-1} + \beta * Z_{c,t} + \gamma * W_{c,t} + Other_{b,c,t}$$

where $y_{b,c,t}$ denotes the headline profitability measures (ROA, ROE) and relevant income components (net interest income, non-interest income) for bank *b*, in country *c*, in year *t*; whereas

[11] See, for example, ECB (2015) and the references therein.

[12] In the presence of scale and scope economies, rising bank concentration may reduce borrowing costs. However, if accompanied by rising market power, greater concentration may under some conditions lead to higher spreads and suboptimal credit volumes. Erel (2011), for example, finds that rising bank concentration increases the cost of financial intermediation. The market concentration measure along with the cost-to-income ratio should capture the implications of (excessive) branch network size and headcounts as well as the lack of sufficient IT investment needed to reap the benefits of greater digitization. Note that impact of size and concentration on profitability are related.

[13] For example, even the updated supervisory indicators by Barth and others (2006) end in 2011. Data coverage also limits the inclusion of indicators that could capture quasi-public competitors (including in some cases, cooperatives) and nonbank competition.

$X_{b,c,t-1}$, $Z_{c,t}$, and $W_{c,t}$, encompass the bank-specific, cyclical, and structural determinants; $Other_{b,c,t}$ includes (bank and time) fixed effects terms and a residual term, respectively. Building on this baseline specification, an array of robustness checks are conducted. More importantly, this specification forms the basis of the quantile regressions used to generate conditional profitability distributions.

Conditional Profitability Distributions

15. The most novel aspect of this chapter is the estimation of conditional bank profitability distributions. In particular, quantile regressions are used to generate profitability distributions conditional on the bank-specific, cyclical, and structural determinants reviewed above. Selected determinants can then be shocked to assess how the shape of the profitability distribution changes—an approach which clearly goes beyond standard comparative statics centered on averages. Importantly, this powerful method can be used to quantify how selected determinants influence the probability of banks' profitability being above and below a certain threshold of interest.

16. The link between profitability and the underlying determinants can be made using quantile regressions. Consider the following simplified specification:

$$y^q_{b,c,t} = \beta^q \Xi_{b,c,t} + \epsilon^q_t$$

where $y^q_{b,c,t}$, $\Xi_{b,c,t}$, ϵ^q_t, and q denote the measure of profitability, the set of (bank-specific, cyclical, and structural) determinants, a residual term (as well as bank and time fixed effects terms), and q denotes various percentiles of interest, for example, q = {0.05; 0.25; 0.50; 0.75; 0.95}, respectively.[14] The estimated conditional quantile function (inverse cumulative distribution function) would in turn correspond to $\hat{y}^q_{b,c,t}(= \hat{\beta}^q \Xi_{b,c,t})$, which is used to generate the conditional profitability distributions.

17. The conditional distribution is estimated by fitting a flexible parametric distribution to the data. Given the noisiness of quantile functions estimates in practice, recovering the corresponding probability density function (PDF) will require smoothing of the quantile function. In line with the approach of Adrian, Boyarchenko, and Giannone (2017), this is accomplished via fitting a (parametric form) 'skewed' t-distribution:[15]

$$f(y;\mu,s,v,\xi) = \begin{cases} \dfrac{2}{\xi + \frac{1}{\xi}} g(z)\xi, & z < 0 \\ \dfrac{2}{\xi + \frac{1}{\xi}} g(z)/\xi, & z \geq 0 \end{cases} \quad (3)$$

[14] On quantile regress analysis, see Koenker and Bassett (1978) and Koenker (2005).

[15] See also, GFSR April 2017 Chapter 2, and GFSR October 2017 Chapter 3.

where $g(z) = \bar{g}(z;\ v)/s$, with $\bar{g}(.)$ denoting the PDF of standard Student-t with v degrees of freedom; z is given by $((y-\mu)/s)$, with μ and s referring to location and scale parameters, respectively. Skewness is governed by shape parameter ξ. This functional form for the skewed t-distribution is based on that motivated by Fernandez and Steel (1998), further explored and refined in Giot and Laurent (2003) and Lambert and Laurent (2002); see also Boudt, Peterson and Croux (2009).[16] For specified values for the conditioning variables, the four parameters $\{\mu, s, v, \xi\}$ of the implied density are pinned down by minimizing the squared distance between the estimated quantile function, $\hat{y}^q$, and theoretical quantile function $y^{q,f}(\mu, s, v, \xi)$ corresponding to the above skewed-t distribution. Specifically, the 5th, 25th, 50th, 75th and 95th percentiles, for example, can be matched via distance minimization:

$$\{\mu, s, v, \xi\} = \underset{\mu,s,v,\xi}{\mathbf{arg}\min} \sum_q \{\hat{y}^q - y^{q,f}(\mu, s, v, \xi)\}^2 \quad (4)$$

where $\mu \in \mathbb{R}$, $s > 0$, $v \geq 2$ and $\xi > 0$. Notwithstanding the skewness property, the choice of a skewed-t functional form is advantageous from the perspective of flexibility. For example, as $v \to \infty$, $f(y; \mu, s, v, \xi)$ is characterized by tail properties resembling a Gaussian; moreover, the density is symmetric when $\xi = 1$.

C. Data, Key Trends, and Stylized Facts

Before proceeding to the formal econometric analysis, this section provides an overview of the data and presents some key stylized facts.

Data

18. Data on large euro area banks is collected from publicly available sources. Balance sheet and income statement information from the FitchConnect database over 2007–2016 are complemented with country-level macroeconomic data and various structural indicators. Following the approach adopted by the European Banking Authority and the ECB, bank statements at the highest level of consolidation were used. The 109 SSM-supervised banks amounted to about €23 trillion in total assets in 2015, the year with the largest number of banks in the sample (Table 1).[17]

19. It is important to recognize several features of the data which can affect the results. First, some indicators may change over time because of merger and acquisition activity. Second, banks that closed during the sample period were excluded bringing about survivorship bias. Third, some banks have sizeable international operation and are thus influenced by global macroeconomic

[16] Alternative specifications for the skewed t-distribution are present in literature, e.g., as put forth inter alia by Hansen (1994) and Azzalini and Capitanio (2003). These are essentially equivalent given a (nonlinear) transformation of the skewness parameter.

[17] Note that the assets of the euro area banking sector stood at about €25 trillion at end-2017 (based on consolidated banking data).

conditions. Fourth, included in the list of significant institutions are those that are more like development banks and do not engage in traditional lending and trading activities.

20. Some of these potential concerns are addressed as follows: First, as discussed below, both bank and time fixed effects terms are included in the baseline regressions. The former accounts for time-invariant bank-specific features and the latter captures regional and global developments that may be important with banks with significant exposures beyond the euro area (and also captures turbulent market conditions). Second, as a robustness check, the regressions are re-estimated using a balanced sample of banks. Third, quantile regressions are considered which are less sensitive to outliers. The baseline specifications are also complemented by an array of robustness checks.

Key Trends and Stylized Facts

21. Average profitability has been on a downtrend since 2007, but there is wide variation among banks:

- To assess key trends more accurately, a balanced sample of 45 SSM-supervised significant institutions (SSM SIs), accounting for 56 percent of sample assets in 2016, is used. Figure 1 displays the median, 25th and 75th percentiles, as well as the weighted average for a few bank-specific variables in this sample over 2007–2016. The two headline measures of profitability, ROA and ROE, have been persistently low over the past decade, but with notable variation across banks. Moreover, banks' average ROE continues to trail market estimates of the cost of equity, and analysts do not expect this situation to change quickly for many banks despite the ongoing recovery. It is also important to recognize recent progress: ROE in 2017Q4 was about 6 percent on average across all SIs.

- Table 2 summarizes some stylized facts that reinforce the concerns associated with euro area bank's profitability. The ROA outturn for 2016, at 0.34 percent, is the same as the sample average and has a sizeable standard deviation. Despite a higher reading relative to the 2007–2016 period, average ROE stood at only 4.1 in 2016. The starker variation across banks partly reflects the fact that small difference in leverage (the inverse of Equity/Assets) could make a significant difference in ROE among banks.

22. Low profitability is pervasive across bank business models. A scatterplot of SSM banks against two indicators—loans-to-assets and deposits-to-assets—enables us to see the distribution of SSM assets by broad business models (Figure 1). Although this two-dimensional business model classification is simplistic and based on coarse proxies, it nevertheless highlights the diversity of the largest euro area banks. Banks in the northeast corner are designated as "traditional" banks with an above-median share of loans-to-assets and deposits-to-assets and comprise €4 trillion in assets. On the other extreme are the "nontraditional" banks that have a large share of trading assets and depend more on wholesale funding. This set of banks includes the euro area global systemically important banks (G-SIBs) and accounts for €14 trillion in assets. Many banks are scattered across these two polar cases. The red dots indicate banks with ROE less than 8 percent, the lower range of the minimum cost-of-equity desired by investors—the incident of low ROE is strewn across a wide variation in business models.

23. NPL and cost-to-income ratios also display significant dispersion across banks. A fallout of the crises in the euro area has been high nonperforming loans across banks (as a share of gross loans, that is, the NPLs ratio), which is coming down gradually, but progress remain uneven (Figure 1).[18] The average NPL ratio remained elevated in 2016, albeit concentrated in some banks, as reflected in the large standard deviation (Table 2). Overhead (non-interest) costs, as a share of operating income, is higher in 2016 compared to the sample average, likely reflecting the inertia of expenses related to large branch networks and servicing of nonperforming loans for traditional banks, and fees and fines for others. Other key bank-specific characteristics vary notably across banks as well.

24. Average GDP growth, which included both the crisis and the recovery, is below to the current estimates of potential growth. Over the 2007–2016 sample that is considered in the analysis, average real GDP growth was 0.8 percent and with wide cross-country differences due to both the global financial crisis and the European debt crisis. In fact, the standard deviation of growth was 3.3 percent as shown in Table 2. In 2016, growth rose to 1.2 percent and its standard deviation declined. This observation is in line with the synchronized nature of the recovery of the euro area countries, with all countries growing, and the variation in growth among countries at the lowest since the advent of the euro. Nevertheless, the IMF World Economic Outlook projects real GDP growth in the euro area to hover about 1½ percent over the medium term, suggesting that the current spurt of growth is likely not permanent in nature.

25. Slicing through the distribution of ROE reveals that the NPL and cost-to-income ratios reveal clear patterns. Table 3 shows the main bank-specific characteristics across four ROE levels in 2016: below the 25^{th} percentile (<Q1), between 25^{th} and 50^{th} percentile (Q1–Q2), between 50^{th} and 75^{th} (Q2–Q3), and above 75^{th} percentile (>Q3). The skewed nature of the ROE distribution is noticeable: the ROE of banks in the left tail have an average of –16 percent. Banks in this end of the distribution have an ROA of –1 percent, an NPL ratio of 22 percent, and a cost-to-income ratio of 81 percent on average and seem to confront similar challenges, but to varying degrees, which tend to be distinct from the other SIs in the sample. Specifically, moving rightwards across the columns uncovers a monotonic decrease in both cost-to-income and NPL ratios.

D. Econometric Analysis

The section presents the OLS and quantile regression results as well as discusses robustness.

Benchmark OLS Regression Analysis

26. The baseline results show that real GDP growth and the NPL ratio, besides total assets, are the most reliable determinants of bank return on assets. Table 4 shows the baseline ROA

[18] More recently, the NPL ratio, for all SIs on average, has declined to 4.9 percent in 2017 from 6.2 percent in 2016.

specification under the first column, as well as key ROA components as dependent variables the shed further light on the main channels driving the results. Other than size, real GDP growth and the NPL ratio appear to be the two statistically significant determinants of ROA. A 1 percentage point increase in growth would raise ROA by 27 basis points. Given that average ROA across banks over 2007-2016 was 34 basis points, this is a notable increase. At the same time, recall that growth over the sample period had an average of 0.8 percent—in other words, the increase in growth is large. The results also indicate that the marginal effect of a 1 percentage point lower NPL ratio is a rise in ROA by 5 basis points. On average, the link between ROA and cost-to-income, concentration, and business model indicators are estimated less precisely. Although differences in sample, specifications, and econometric methodology, render comparisons difficult, overall, these findings are broadly similar to those of the studies discussed above.

27. The components of ROA were then used as dependent variables to explore the channels at play. Higher growth results in a rise in noninterest revenue streams (Table 4) and a decline in loan-loss provisioning (column 4). Lower NPL ratios would reduce provisioning costs and, hence, increase ROA. Note also that 60 percent of the effect of lagged NPLs on ROA stem from the provisioning needs (based on column 1 and column 4).

Robustness Analysis

28. Growth and NPLs remain significant determinants of profitability even as other variables are included in the baseline specification (Table 5). Various additional variables are added to the baseline ROA to assess the robustness of the main results. Bank-, country-, and region-specific variables groups are considered. For the first group, bank-specific loan growth and the change in the NPL ratio are considered. The second group includes country-specific measures of the slope of the yield curve (the difference between the 5-year and 3-month government bond yields) and FCIs. The FCI measures the ease of obtaining financing relative to each country's history, see Arregui and others (2018) for further details. The third group includes a single variable, namely the area-wide level of the short-term interest rate (the ECB estimate of the 3-month zero-coupon yield on AAA securities). The baseline specification is also re-estimated using a balance sample as well as with the general method of moments (GMM).

29. The change in the NPL ratio is a significant determinant but strongly correlated with GDP growth. When added, the change in the NPL ratio is statistically significant and has the expected sign. Therefore, both the stock and the flow of NPLs act as a drag on profitability owing to servicing costs and the reduced availability of funds to lend. Since the GDP growth term is included and attention focuses on medium-term effects, the term is not included in further analysis.

30. A steeper yield curve or higher short-term interest rates do not appear to help profitability of these banks on average. The slope of the yield curve is an indicator of the intermediation margin given by the spread between lending and funding rates. All else equal, a steeper yield curve would raise net interest income. However, higher long-term interest rates would reduce the valuations of longer-term securities (that are held in the available-for-sale portfolio for instance). Since the crisis, the maturity of such securities held by banks have gone up, and so the valuation effects are sizeable even as net interest income improves with higher long-term interest rates. Furthermore, higher interest rates could push highly indebted bank borrowers to default on their loan payments that would increase provisioning costs and decrease profitability. Likewise, bank profitability and short-term interest rates are positively correlated, but this correlation is not statistically significant.

31. Tighter financial conditions tend to adversely affect bank earnings. Recall that the FCI discussed above contains various spreads and can therefore affect bank profitability in at least two ways: First, a spike in spreads would result in valuations losses (on holdings of both corporate and government securities). Second, funding costs are likely to rise faster than lending rates, thereby compressing interest margins.

32. Including a lagged dependent variable or using a balanced sample highlight the robustness of the main findings. Following the ECB (2015) and Das and Xu (forthcoming), a lagged dependent variable is included in the baseline and the model is estimated using the GMM estimator developed by Arellano and Bond (1991). There are two main takeaways from these results: First, the lagged dependent variable is statistically insignificant (Table 5). It also has a negative coefficient, perhaps a reflection of large yearly fluctuations in profitability possibly owing to the crisis experiences. Second, the GMM results are consistent with the baseline specification. For example, both the "short-run" coefficients and their "long-run" counterparts are broadly in line with those in the other specifications. Note also that re-estimation using a balanced sample produces results very similar to the baseline specification.

33. Using ROE yields broadly similar findings. The regressions discussed above were estimated using ROE as the main profitability indicator and again indicate the growth and the NPL ratio are the robust determinants (Table 6). Although total assets cease to be a significant determinant, the change in the NPL ratio gains in significance. As will be discussed below, the OLS regressions may mask underlying non-linear relationships, which motivates the use of quantile regression analysis.

34. A final robustness check considered risk-adjusted profitability metrics. Following Demirguc-Kunt and Huizinga (2010), the z-score (also interpreted as a measure of bank risk) is considered. The z-score reflects the number of standard deviations that a bank's rate of ROA must fall for the bank to become insolvent. It is constructed as the sum of the mean rates of ROA and the equity-to-assets ratio divided by the standard deviation of ROA (Roy, 1952). A higher z-score signals a lower probability of bank insolvency. In addition, risk-adjusted variants of ROA and ROE are considered whereby each profitability metric is scaled by its respective standard deviation (broadly analogous to a Sharpe ratio). The entire 2007–2016 sample was used to calculate the needed standard deviations as accurately as possible. This transforms the panel data set into a cross-section (thereby losing many degrees of freedom). Regressions using the full set of banks and the balanced set of banks are shown in Table 7. Note that the NPL ratio is highly statistically significant, whereas the correlation between growth and risk-adjusted profits is less precisely estimated in the cross-section.

Quantile Regression Analysis

35. Quantile regressions reveal that growth and the NPL ratio remain the most robust determinants of bank profitability. The results for three quantiles (25, 50, and 75) are reported for ROA and ROE in Table 8 and Table 9, respectively. To facilitate comparisons, the baseline OLS specification is shown in the first column in each table. For both profitability metrics, growth and the NPL ratio have the expected signs and are statistically significant across all quantiles. Notably, the (absolute value of the) coefficients on growth and NPLs decrease monotonically across the 25th to the 75th quantiles in both sets of regressions. For example, in the ROA regressions, the growth coefficient is 0.2 versus 0.09 in the 25th and 75th quantile regressions, respectively. A similar pattern holds in the case of the NPL ratio. These findings suggest that banks with the greater profitability challenges stand to benefit the most from an increase in GDP growth and from lower NPL ratios.

36. In contrast to the OLS regressions, the quantile regressions suggest that improved operational efficiency is important for bank profitability. The quantile regressions indicate that lower cost-to-income ratios are associated with higher ROA for banks outside of the weakest end of the profitability spectrum.[19] Changes to business models hold promise as well. Evidence points to a positive correlation between ROA and a greater deposit-to-asset ratio.

E. Conditional Profitability Distributions

As the most novel part of this study, this section discusses the conditional profitability distributions and how shocks to the underlying bank-specific determinants alter the shape of these distributions.

37. Quantile regressions are used to generate conditional profitability distributions. The illustrative ROE distributions are conditional on the determinants included in the quantile regressions discussed above (which are evaluated at their respective sample means). Note that the 2007-2016 sample period includes several crisis episodes and does not account for the more recent improvements in bank profitability noted previously.[20] The distribution has a mean of 5 percent and a sizeable standard deviation of 20 percent.[21] The shape of the conditional distribution is particularly noteworthy as it has a long-left tail highlighting the pervasiveness of low profitability across SSM banks (Figure 2).[22]

[19] The lack statistical significance for the 25th percentile likely reflects the considerable heterogeneity of banks even in the weaker tail of the ROA distribution.

[20] For example, ROE increased from 3.29 percent in 2016Q4 to 5.98 percent at end-2017. Note that the specifications include time fixed effects terms which account for crisis periods, but that they do not include FCIs (to keep the quantile regressions as parsimonious as possible).

[21] The ROE data was winsorized to facilitate the visual representation of the conditional distributions and do not change the qualitative conclusions. In the end, the tails were winsorized by 7.5 percent, though 5 percent and 2.5 percent winsorization was also considered.

[22] Conditional ROA distributions are available upon request, reveal broadly similar findings. These were omitted for brevity, but also because ROE can be readily compared to market estimates of the cost of equity.

38. The shape of the conditional ROE distributions change when the underlying determinants are shocked, revealing insightful patterns. Recall that the two most reliable profitability determinants were growth and NPLs. In what follows, these two determinants are now shocked to assess how these changes affect profitability. Importantly, the analysis goes beyond the impact on average profitability, but rather considers how changes in these determinants influence the entire ROE distribution. For instance, greater growth (a positive 2 standard deviation increase relative to the sample average), pulls the distribution to the right. Likewise, a lower NPL ratio (a negative 2 standard deviation decrease relative to the sample average) results in a broadly similar shift to the right as well. However, in both cases, the skewed nature of the shocked distributions is intact: the long-left tail remains, but the area under it accounts for less mass.

39. The conditional distributions can be used to make quantitative assessments. For illustrative purposes, and motivated by the stylized facts discussed earlier, the probabilities of ROE above and below the 8 percent threshold are now computed. The framework is flexible in that it can easily accommodate other thresholds as well. These probabilities are shown in Table 10 which comprises of two columns (below and above 8 percent ROE, respectively). The first row depicts these probabilities under the baseline distribution, while the next three rows tabulate the probabilities in response to 1 standard deviation shocks: higher growth, a lower NPL ratio, or their combination.

40. These illustrative simulations suggest that the combination of a decisive reduction of NPLs amid a strong recovery could significantly increase banks' profitability prospects:

- Under the baseline distribution, the probably of any bank in the sample with ROE less than 8 percent is around 77 percent. While not shown, there is a fifty-fifty chance that a banks' profitability lies in negative territory.[23]

- Greater growth reduces the likelihood of ROE below 8 percent to around 63 percent, and raises the probability of a bank with ROE greater than 8 percent by 13 percentage points (to around 37 percent). In this scenario, the likelihood of a bank with negative profitability declines to about 35 percent. Hence, while higher growth would naturally raise banks' profitability prospects, note that the shock under consideration is large: in the 2007–2017 period, average growth was 0.8 percent and had a standard deviation of 3.3 percent.

- The quantitative effects of a 1 standard deviation decrease in the NPL ratio—which is large at almost 9 percentage points—results in broadly similar changes in terms of probabilities and, interestingly, in terms of how the contours of the distributions change.

- The implications of a joint shock, whereby growth increases by one standard deviation and the NPL ratio decrease by the same magnitude, are now investigated. Three distributions are shown: the baseline, the distribution where on growth is shocked, and the distribution where both

[23] Recall that these distributions are based on all banks over 2007–2016 which includes episodes of turbulent market conditions. At the same time, winsorization of the ROE data reduces the impact of extremely negative earning outturns on the results.

growth and NPLs are shocked. The last distribution could be interpreted a simple simulation of an aggressive NPL reduction in the context of a robust economic upswing. The distribution reflecting the joint shocks indicates that the probability of a bank with ROE less than 8 percent now declines to about 50 percent. Moreover, the likelihood of a bank with negative profitability is about 25 percent.

F. Weakest Bank Profits in 2016—An Illustrative Exercise

In this section, an illustrative exercise is conducted to shed further light on the following question: Can the weakest banks in 2016 turn around with higher growth?

41. A complementary exercise focuses on the banks with the lowest ROE outturns in 2016. Specifically, the analysis re-estimates the baseline OLS regressions discussed above using the bottom third of the ROE distribution.[24] These regressions are shown in Table 11, and the ROE displays strong correlations with both GDP growth and NPL ratios.

42. The simulations indicate that higher GDP growth is likely to lift the profitability of the weakest banks into positive territory. The coefficients for growth (11.61) and NPL ratio (–1.18) from Table 11 are used to compute comparative statics of ROE for the banks that have lower than 33rd percentile of ROE.[25] The results for these banks are shown in Figure 3, with a table that shows the average profitability (–6.5) and NPL ratio (18.9) of this group of banks in 2016, and the NPL ratio in 2007 (3.9). This group of banks comprised €5½ trillion in total assets in 2016. Starting from an ROE of –6.5 percent in 2016 (blue bar), a 1 percentage point higher GDP growth would lift the ROE to positive territory to 5.1 percent (–6.5 + 11.61*[ΔGDP growth = 1 percentage point]). But, growth will not be enough to move the ROE of these banks to above the 8 percent threshold.

43. The least profitable banks are most likely to turn around with drastic NPL resolution. In line with the findings from the conditional profitability distributions in the previous section, Figure 3 shows that aggressive NPL reductions would help. If the NPL ratio were to be reduced from 18.9 percent to the 2007 level of 3.9 percent, using work-outs, sales, restructuring or resolution tools, then the average ROE of these weakest banks would rise to 11.1 percent (–6.5 – 1.18 * [ΔNPL ratio = 3.9 – 18.9 = 15 percentage points]) and clearly above cost of equity estimates. The ROE would be even higher if the NPL ratio were to be reduced while GDP growth is high.[26]

[24] Using banks with below-median ROE result in qualitatively similar findings. Given that the sample ends in 2016, this illustrative exercise do not account for the improvement in ROE across all SIs in 2017.

[25] A related exercise was conducted by Jobst and Weber (2016) for major Italian banks. See also Kamiar, Raissi, and Weber (2017).

[26] A possible caveat is that drastic NPL resolution would have implications for capitalization of these banks, which is taken as given in this simple illustrative exercise. If un-provisioned NPLs were to be removed from the balance sheet, the capital ratio would fall and would adversely affect ROE. In addition, there are possible second-round effects to reducing NPL stock too rapidly that may reduce growth and attenuate the expected benefits. Likewise, the pace of NPL reduction is also partly depending on banks' capital positions and ability to raise capital.

G. Conclusions and Policy Implications

44. This study attempts to shed light on the main determinants of the profitability of larger euro area bank using novel approaches. Empirical analysis of 109 SIs over 2007–2016 reveals that real GDP growth and the NPL ratio are the most reliable medium-term determinants of profitability. The study then proposes an innovative approach to quantify how persistent changes in such determinants affect the shape of the conditional profitability distribution, and thus goes beyond standard comparative statics analysis which focuses on average responses.

45. The results suggest that the ongoing economic recovery will support profitability in general, but it is unlikely to resolve the structural challenges faced by the least profitable banks in the sample. Although higher growth would raise profits on average, a large swath of banks with the weakest profitability would continue to struggle even with a robust recovery. Therefore, banks should take advantage of the current upswing by resolutely addressing their NPL stocks—such a strategy holds the most promise for weak banks' profitability prospects. In addition, evidence suggests that greater cost efficiency (through digitalization, for example) could enhance profitability of many banks, and should be combined with a tailored approach to updating business models.

Table 1. Euro Area Bank Sample
(Total Assets in billions of euros)

Bank	CTY	Total Assets
Erste Group Bank AG	AT	217.5
Raiffeisen Bank International AG	AT	124.6
BAWAG Holding GmbH	AT	38.9
Sberbank Europe AG	AT	15.6
Volksbank Wien AG	AT	10.9
VTB Bank (Austria) AG	AT	9.2
KBC Group NV	BE	274.7
Dexia	BE	250.7
Belfius Bank SA/NV	BE	192.7
Argenta B.V.G. NV	BE	43.3
Bank of New York Mellon S.A./N.V.	BE	38.6
AXA Bank Europe	BE	33.7
Bank of Cyprus Public Company Limited	CY	25.3
Cooperative Central Bank Ltd.	CY	15.5
RCB Bank Ltd	CY	14.6
Hellenic Bank Public Company Limited	CY	8.1
Swedbank AS	EE	10.5
AS SEB Pank	EE	5.7
Nordea Bank Finland Plc	FI	328.4
OP Financial Group	FI	135.5
Danske Bank PLC	FI	33.0
BNP Paribas S.A.	FR	2171.1
Credit Agricole	FR	1849.6
Credit Mutuel	FR	805.5
BPCE S.A.	FR	788.4
La Banque Postale	FR	238.1
HSBC France	FR	183.4
SFIL	FR	91.1
Bpifrance Financement S.A.	FR	48.6
Caisse de Refinancement de l'Habitat (CRH)	FR	46.4
RCI Banque	FR	40.4
Agence Francaise de Developpement (AFD)	FR	39.0
Barclays France SA	FR	0.0
Deutsche Bank AG	DE	1773.7
Commerzbank AG	DE	580.0
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	DE	444.6
Landesbank Baden-Wuerttemberg	DE	254.8
Bayerische Landesbank	DE	234.9
Norddeutsche Landesbank Girozentrale	DE	197.1
Landesbank Hessen-Thueringen Girozentrale	DE	187.5
NRW.BANK	DE	151.9
Volkswagen Financial Services AG	DE	132.0
DekaBank Deutsche Girozentrale	DE	117.6
HSH Nordbank AG	DE	105.6
Landwirtschaftliche Rentenbank	DE	101.6
Erwerbsgesellschaft der S-Finanzgruppe mbH & Co KG	DE	81.9
Deutsche Pfandbriefbank AG	DE	72.7
Aareal Bank AG	DE	56.6
HASPA Finanzholding	DE	49.4
Muenchener Hypothekenbank eG	DE	41.5
State Street Bank International GmbH	DE	40.9
Deutsche Apotheker- und Aerztebank eG	DE	39.7
SEB AG	DE	24.4
National Bank of Greece S.A.	GR	121.0
Piraeus Bank S.A.	GR	95.7
Eurobank Ergasias S.A.	GR	80.1
Alpha Bank AE	GR	75.4

Bank	CTY	Total Assets
Bank of Ireland	IE	142.6
Allied Irish Banks, plc	IE	112.3
Ulster Bank Ireland DAC	IE	33.8
Citibank Europe Plc	IE	24.0
UniCredit S.p.A.	IT	936.8
Intesa Sanpaolo S.p.A.	IT	736.5
Banco BPM S.p.A.	IT	186.6
Banca Monte dei Paschi di Siena SpA	IT	184.0
Unione di Banche Italiane S.p.A.	IT	127.6
Mediobanca Spa	IT	79.1
BPER Banca S.p.A.	IT	66.7
Iccrea Holding SpA	IT	53.0
Banca Popolare di Vicenza	IT	43.3
Credito Emiliano S.p.A.	IT	40.8
Banca Popolare di Sondrio-Societa' Cooperativa per Azioni	IT	38.7
Veneto Banca S.p.A.	IT	36.3
Banca Carige S.p.A. - Cassa di Risparmio di Genova e Imperia	IT	33.0
Swedbank AS (Latvia)	LV	5.9
ABLV Bank AS	LV	5.4
AS SEB Banka	LV	3.9
Banque et Caisse d'Epargne de l'Etat	LU	46.6
Precision Capital S.A.	LU	35.6
JP Morgan Bank Luxembourg S.A.	LU	11.3
HSBC Bank Malta plc	MT	7.9
ING Group	NL	1094.4
Cooperatieve Rabobank U.A.	NL	739.1
ABN AMRO Group N.V.	NL	443.5
Bank Nederlandse Gemeenten (BNG)	NL	162.8
Nederlandse Waterschapsbank NV	NL	99.4
de Volksbank N.V.	NL	68.3
Caixa Geral de Depositos, S.A.	PT	109.9
Banco Comercial Portugues, S.A.	PT	81.5
Novo Banco, S.A.	PT	62.6
Slovenska Sporitelna	SK	15.2
Vseobecna Uverova Banka	SK	13.7
Tatra Banka	SK	12.2
Nova Ljubljanska banka d.d.	SI	12.9
Abanka d.d.	SI	4.2
Banco Santander, S.A.	ES	1459.2
Banco Bilbao Vizcaya Argentaria, S.A.	ES	816.4
Criteria Caixa, S.A., Unipersonal	ES	387.5
BFA, Tenedora de Acciones, S.A.U.	ES	232.7
Banco de Sabadell	ES	227.1
Banco Popular Espanol S.A.	ES	172.7
Unicaja Banco S.A.	ES	65.7
Ibercaja Banco, S.A.	ES	64.1
Bankinter	ES	63.9
Kutxabank, S.A.	ES	63.6
ABANCA Corporacion Bancaria, S.A.	ES	51.5
Liberbank S.A.	ES	45.9
Banco Mare Nostrum S.A.	ES	44.4
Banco de Credito Social Cooperativo, S.A.	ES	10.3
Total assets		22804.9

Notes: CTY: Country; AT: Austria: BE: Belgium; CY: Cyprus; EE: Estonia; FI: Finland; FR: France; DE: Germany; GR: Greece; IT: Italy; LV: Latvia; LU: Luxembourg; MT: Malta; NL: Netherlands; PT: Portugal; SK: Slovakia; ES: Spain. Assets for 2015 shown because that is the year when the number of banks (109) is greatest in the unbalance (2007-2016) sample.

Table 2. Descriptive Statistics of Main Variables

		2007-2016				2016		
Variable description	**Variable**	**# obs**	**Median**	**Mean**	**SD**	**Median**	**Mean**	**SD**
Return on average assets	ROA	1047	0.42	0.33	1.60	0.47	0.34	1.20
Return on average equity	ROE	1047	8.19	2.08	49.73	8.20	4.03	15.98
log (Assets)	logA	1081	11.29	11.35	1.62	11.13	11.21	1.44
Equity/Assets	equitytoassets	1081	5.93	6.95	7.16	7.08	7.80	3.83
Real GDP growth	gdpgrowth	967	1.19	0.79	3.34	1.86	2.08	1.17
3-month zero coupon yield on AAA euro area securities (ECB)	ECBAAA3M	1081	0.41	0.94	1.50	-0.62	-0.62	0.00
Ratio of Nonperforming Loans/Gross Loans	NPLratio	898	4.3	7.75	9.61	4.88	10.63	13.57
Overhead cost/Operating Income	costtoincome	1080	59.9	35.54	743.83	62.65	66.11	23.08
Total Loans/Total Assets	loanstoassets	1065	62.73	58.15	22.11	64.70	59.07	20.63
Total Customer Deposits/Total Assets	depositstoassets	1045	44.76	44.69	22.11	53.06	52.12	22.27
Noninterest Revenues/Total Operating Income	noninterestincomegrossrevenues	1077	33.11	35.57	160.33	36.89	35.29	34.32
Share of 5-largest bank assets in total bank assets (Country-specific)	Largest5	1081	47.4	52.03	19.76	45.95	54.44	18.95

Sources: FitchConnect, ECB, and IMF staff calculations.

Table 3. Stylized Facts: Key Bank-Specific Determinants

	ROE quintile buckets, 2016			
Variables	**<Q1**	**Q1–Q2**	**Q2–Q3**	**>Q3**
ROE	-16.3	5.7	9.9	15.3
ROA	-1.1	0.4	0.8	1.3
Equity/Assets	8.3	7.4	7.7	8.5
Total Assets (trillions of euros)	4.1	5.0	8.3	3.5
NPL ratio	22.3	11.2	5.3	4.2
Cost/Income	81.2	70.2	61.7	52.2
Loans/Assets	67.9	58.7	51.1	66.0
Deposits/Assets	51.5	48.4	47.2	59.0

Sources: FitchConnect, ECB, and IMF staff calculations.

Notes: The numbers in the columns are the mean of the variables in each quintile bucket, which is based on the distribution of the ROE across banks in 2016.

Table 4. Baseline Profitability Regressions: Return on Assets and Components

VARIABLES	(1) ROA	(2) Net Interest Income/A	(3) Noninterest income/A	(4) Loan loss provisions/A
L.logA	-0.532**	-0.106	-0.265***	0.210
	(0.259)	(0.0969)	(0.0667)	(0.252)
L.equitytotalassets	0.0314	0.0446***	-0.00335	-0.0138
	(0.0454)	(0.00789)	(0.00688)	(0.0384)
gdpgrowth	0.272***	0.00542	0.0111*	-0.199***
	(0.0681)	(0.00770)	(0.00616)	(0.0348)
L.nplratio	-0.0457**	-0.00407	-0.000394	0.0283*
	(0.0217)	(0.00423)	(0.00442)	(0.0167)
L.costtoincome	-0.00304	-0.00139***	0.000141	0.00173
	(0.00219)	(0.000491)	(0.000361)	(0.00165)
L.loanstoassets	-0.0134	0.00609**	-0.000838	0.0194
	(0.0141)	(0.00260)	(0.00215)	(0.0124)
L.depositstoassets	0.00791	0.00501*	0.00229	-0.0160**
	(0.0106)	(0.00256)	(0.00260)	(0.00798)
L.noninterestincomegrossrevenues	-0.00206	-0.00108**	0.000348	0.00131
	(0.00161)	(0.000435)	(0.000283)	(0.00120)
largest5	-0.00937	-0.00421	0.00116	0.0218*
	(0.0213)	(0.00427)	(0.00416)	(0.0126)
Observations	794	794	794	791
R-squared	0.482	0.904	0.662	0.480

Note: Bank and year fixed effect terms not shown; standard errors clustered by country*year.
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Robustness Analysis: Return on Assets

	(1)	(2)	(3)	(4)	(5)	(6)	(Balanced)	(GMM)
L.logA	-0.532**	-0.587**	-0.570*	-0.557*	-1.211***	-0.482*	-0.741**	0.810
	(0.259)	(0.244)	(0.296)	(0.283)	(0.448)	(0.252)	(0.333)	(0.662)
L.equitytotalassets	0.0314	0.00611	0.0571	0.0103	-0.0680	0.0460	0.0734	0.322***
	(0.0454)	(0.0460)	(0.0582)	(0.0560)	(0.0644)	(0.0442)	(0.0702)	(0.0591)
gdpgrowth	0.272***	0.187***	0.269***	0.225**	0.306**	0.177***	0.353***	0.159***
	(0.0681)	(0.0710)	(0.0729)	(0.0878)	(0.121)	(0.0360)	(0.114)	(0.0388)
L.nplratio	-0.0457**	-0.0711***	-0.0557***	-0.0568**	-0.0622**	-0.0426*	-0.0695***	-0.0847***
	(0.0217)	(0.0196)	(0.0203)	(0.0270)	(0.0262)	(0.0223)	(0.0232)	(0.0219)
L.costtoincome	-0.00304	-0.00165	-0.000487	-0.00200	-0.000104	-0.00375*	-0.00332	-0.0109**
	(0.00219)	(0.00230)	(0.00313)	(0.00246)	(0.00282)	(0.00221)	(0.00370)	(0.00479)
L.loanstoassets	-0.0134	-0.00435	-0.0152	-0.00455	-0.00552	-0.0156	-0.0193	-0.0122
	(0.0141)	(0.0142)	(0.0180)	(0.0178)	(0.0241)	(0.0137)	(0.0166)	(0.0220)
L.depositstoassets	0.00791	-0.00275	0.00190	0.00309	0.00833	0.0114	-0.00433	0.0302**
	(0.0106)	(0.00944)	(0.0129)	(0.0133)	(0.00928)	(0.0105)	(0.0181)	(0.0150)
L.noninterestincome-	-0.00206	-0.00112	-0.000100	-0.00129	0.000104	-0.00227	-0.00207	-0.00930***
-grossrevenues	(0.00161)	(0.00166)	(0.00240)	(0.00184)	(0.00210)	(0.00164)	(0.00276)	(0.00321)
largest5	-0.00937	0.00835	-0.00401	0.0118	-0.0166	-0.0159	0.00193	-0.00431
	(0.0213)	(0.0198)	(0.0273)	(0.0226)	(0.0197)	(0.0223)	(0.0234)	(0.0210)
D.nplratio		-0.154**						
		(0.0607)						
L.loangr			-1.78e-06					
			(1.90e-06)					
FCI				-0.390**				
				(0.174)				
ispctry					-0.0140			
					(0.0265)			
ECBAAA3M						0.0392		
						(0.0474)		
L.ROA								-0.172
								(0.110)
Observations	794	787	718	650	545	794	444	696
R-squared	0.482	0.545	0.486	0.467	0.489	0.433	0.548	

Notes: Bank and year fixed effect terms not shown; standard errors clustered by country*year. Column (6) does not have time fixed effects. For the GMM column only profitability is lagged.
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Return on Equity Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(Balanced)	(GMM)
L.logA	-5.923	-7.337	-14.83	-2.610	-24.68	-4.493	-15.44	19.71
	(12.44)	(12.29)	(14.98)	(16.47)	(23.63)	(11.40)	(12.67)	(21.30)
L.equitytotalassets	-0.0338	-0.578	0.815	-0.0794	-1.581	0.567	-0.866	7.073*
	(1.392)	(1.323)	(1.946)	(1.921)	(1.671)	(1.477)	(2.174)	(3.729)
gdpgrowth	4.329**	2.502	3.842**	3.452	4.596	2.915***	5.671*	1.551*
	(1.681)	(1.619)	(1.707)	(2.286)	(3.328)	(0.812)	(2.937)	(0.872)
L.nplratio	-0.416	-0.961**	-0.728**	-0.890*	-1.180*	-0.378	-0.836**	-1.682**
	(0.422)	(0.383)	(0.364)	(0.516)	(0.699)	(0.419)	(0.359)	(0.721)
L.costtoincome	0.0523	0.0814	0.109	0.0708	0.0772	0.0199	-0.114	-0.248
	(0.119)	(0.115)	(0.244)	(0.141)	(0.169)	(0.118)	(0.0807)	(0.325)
L.loanstoassets	0.217	0.405	-0.0411	0.431	-0.0328	0.128	-0.0880	1.704*
	(0.527)	(0.531)	(0.678)	(0.791)	(1.401)	(0.508)	(0.383)	(1.012)
L.depositstoassets	0.137	-0.0976	-0.0723	0.0692	0.301	0.287	-0.232	0.709
	(0.279)	(0.274)	(0.263)	(0.362)	(0.389)	(0.310)	(0.296)	(0.596)
L.noninterestincome--grossrevenues	0.0379	0.0575	0.0757	0.0522	0.0577	0.0235	-0.0841	-0.178
	(0.0866)	(0.0829)	(0.180)	(0.102)	(0.123)	(0.0852)	(0.0632)	(0.246)
largest5	0.425	0.810	0.579	0.930	0.936	0.373	0.135	0.112
	(0.526)	(0.514)	(0.715)	(0.661)	(0.896)	(0.556)	(0.470)	(0.661)
D.nplratio		-3.318***						
		(1.082)						
L.loangr			-8.08e-06					
			(4.33e-05)					
FCI				-9.982				
				(8.820)				
ispctry					0.0759			
					(1.478)			
ECBAAA3M						2.366		
						(1.511)		
L.ROE								-0.0417
								(0.0602)
Observations	794	787	718	650	545	794	444	696
R-squared	0.220	0.246	0.217	0.207	0.224	0.189	0.360	

Notes: Bank and year fixed effect terms not shown; standard errors clustered by country*year. Column (6) does not have time fixed effects. For the GMM column only profitability is lagged.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness Analysis: Risk-Adjusted Profitability Measures

	ROA/SD		ROE/SD		Z	
	(1)	(2)	(1)	(2)	(1)	(2)
VARIABLES	roa_sdadj	roa_sdadj_bal	roe_sdadj	roe_sdadj_bal	z	z_bal
logA_l_m	-0.0107	-0.663	0.0695	-1.176*	-2.130	-6.517
	(0.506)	(0.617)	(0.703)	(0.629)	(5.782)	(6.798)
gdpgrowth_m	0.0806	-0.00968	0.0734	1.209	-0.418	-5.729
	(0.195)	(0.974)	(0.209)	(1.310)	(2.297)	(7.524)
nplratio_l_m	-0.331***	-0.380***	-0.355***	-0.375***	-2.928***	-3.774***
	(0.0578)	(0.0795)	(0.0673)	(0.0733)	(0.568)	(0.822)
costtoincome_l_m	-0.000401	-0.0919*	0.00181	-0.0766	0.0369	-0.461
	(0.00299)	(0.0538)	(0.00392)	(0.0519)	(0.0458)	(0.531)
loanstoassets_l_m	0.00520	-0.0968*	-0.00186	-0.0561	-0.457	-0.877
	(0.0424)	(0.0505)	(0.0402)	(0.0409)	(0.488)	(0.617)
depositstoassets_l_m	0.0928**	0.116*	0.101***	0.0613	0.368	0.924
	(0.0358)	(0.0624)	(0.0373)	(0.0439)	(0.567)	(0.769)
nonintincrev_m	0.00607	-0.0450	-0.0123	-0.103**	-0.204	-0.330
	(0.0216)	(0.0373)	(0.0282)	(0.0411)	(0.319)	(0.397)
Constant	2.827	24.10**	2.802	30.88***	129.4	229.1*
	(7.090)	(10.69)	(10.04)	(9.880)	(105.5)	(115.5)
Observations	88	45	88	45	88	45
R-squared	0.308	0.569	0.198	0.547	0.208	0.462

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Quantile Regressions: Return on Assets

	OLS	Quantile regressions		
	(1)	(2)	(3)	(4)
VARIABLES		25th	50th	75th
logA_l	-0.532**	-0.221	-0.111	-0.252**
	(0.259)	(0.316)	(0.216)	(0.117)
equitytotalassets_l	0.0314	0.0229	0.0504***	0.0439***
	(0.0454)	(0.0279)	(0.0191)	(0.0103)
gdpgrowth	0.272***	0.201***	0.135***	0.0864***
	(0.0681)	(0.0258)	(0.0176)	(0.00955)
nplratio_l	-0.0457**	-0.0752***	-0.0455***	-0.0103**
	(0.0217)	(0.0113)	(0.00772)	(0.00418)
costtoincome_l	-0.00304	-0.00202	-0.00312**	-0.00192***
	(0.00219)	(0.00192)	(0.00131)	(0.000710)
loanstoassets_l	-0.0134	-0.0118	-0.00949	-0.00639*
	(0.0141)	(0.00953)	(0.00650)	(0.00352)
depositstoassets_l	0.00791	0.00837	0.00531	0.00888**
	(0.0106)	(0.00985)	(0.00672)	(0.00364)
noninterestincomegrossrevenues_l	-0.00206	-0.00122	-0.00230**	-0.00145***
	(0.00161)	(0.00150)	(0.00102)	(0.000553)
largest5	-0.00937	-0.0171	-0.0142	-0.0148***
	(0.0213)	(0.0135)	(0.00921)	(0.00499)
Observations	794	798	798	798

Notes: Bank and year fixed effects no shown.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Quantile Regressions: Return on Equity

	OLS	Quantile regressions		
	(1)	(2)	(3)	(4)
VARIABLES		25th	50th	75th
logA_l	-5.923	-7.343	-5.167	-5.088***
	(12.44)	(7.418)	(3.486)	(1.733)
equitytotalassets_l	-0.0338	0.0709	-0.152	-0.606***
	(1.392)	(0.655)	(0.308)	(0.153)
gdpgrowth	4.329**	3.372***	1.864***	1.045***
	(1.681)	(0.606)	(0.285)	(0.142)
nplratio_l	-0.416	-0.863***	-0.438***	-0.151**
	(0.422)	(0.265)	(0.125)	(0.0620)
costtoincome_l	0.0523	-0.0257	-0.00930	0.0158
	(0.119)	(0.0451)	(0.0212)	(0.0105)
loanstoassets_l	0.217	-0.227	-0.125	-0.113**
	(0.527)	(0.224)	(0.105)	(0.0522)
depositstoassets_l	0.137	0.0660	0.0256	0.0960*
	(0.279)	(0.231)	(0.109)	(0.0540)
noninterestincomegrossrevenues_l	0.0379	-0.0290	-0.00749	0.00964
	(0.0866)	(0.0351)	(0.0165)	(0.00820)
largest5	0.425	-0.355	-0.264*	-0.151**
	(0.526)	(0.317)	(0.149)	(0.0740)
Observations	794	798	798	798

Notes: Bank and year fixed effects no shown.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Summary: Conditional Profitability (ROE) Distributions

(in percent)

ROE threshold:	<8	>8
Baseline	76.9	23.1
Higher Growth	63.1	36.9
Lower NPLs	66.8	33.2
Higher growth and Lower NPLs	52.7	47.3
Descriptive statistics	Mean	Standard deviation
Growth	0.8	3.3
NPL	7.4	8.9

Source: Authors' calculations.

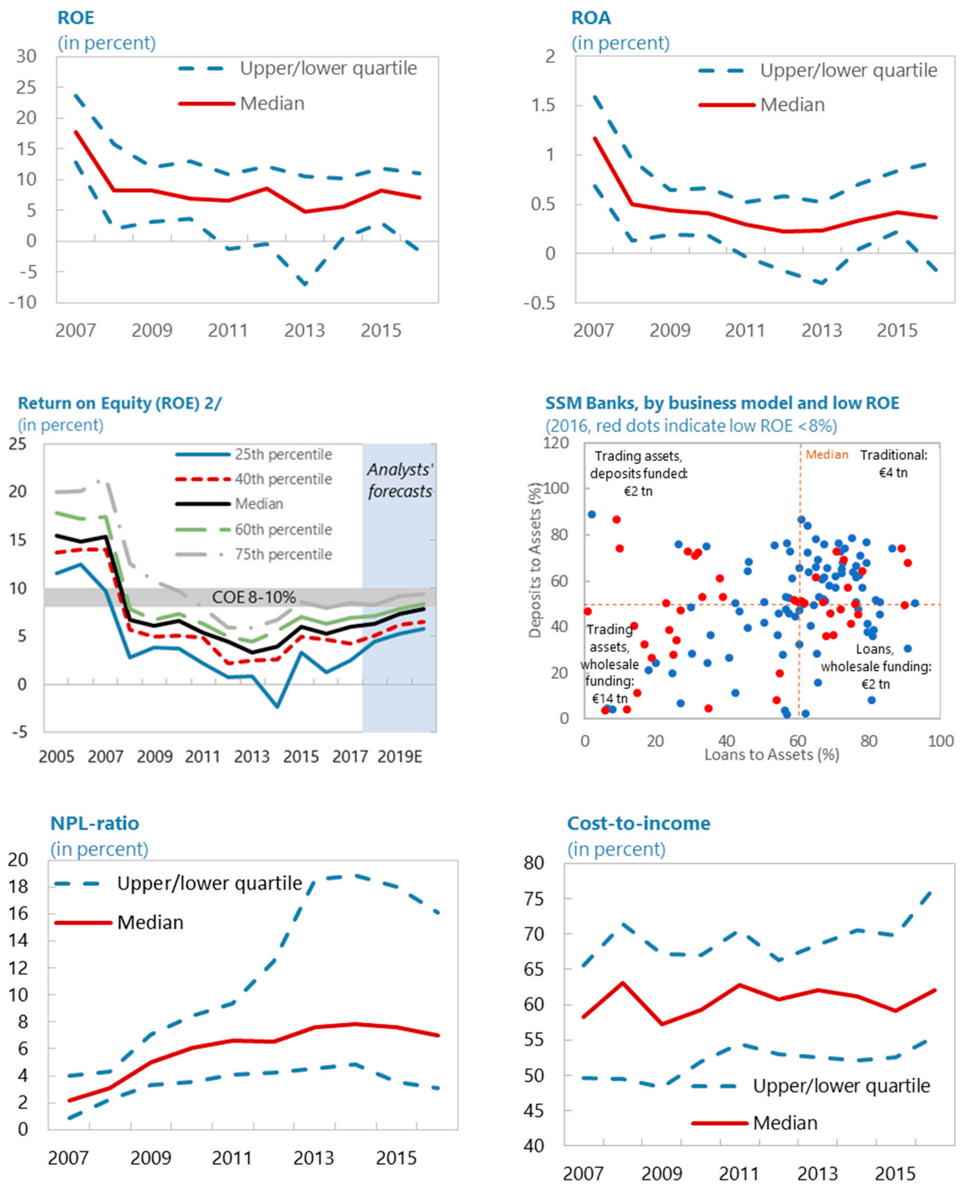
Notes: Return on equity (ROE) is the measure of profitability used. The table displays to probability of ROE being less (greater) than 8 percent. These probabilities are calculated using the baseline and shocked distributions, where 1 standard deviation shocks are used. Selected sample descriptive statistics are included.

Table 11. Profitability Regressions: A Focus on Weaker Banks

VARIABLES	(1) ROE<33rd percentile	(2) ROE<50th percentile
L.logA	2.897	9.119
	(39.07)	(19.43)
L.equitytotalassets	5.824*	2.916
	(3.471)	(2.357)
gdpgrowth	11.61	8.775**
	(7.238)	(3.629)
L.nplratio	-1.178*	-1.266**
	(0.628)	(0.551)
L.costtoincome	0.162	-0.0325
	(0.203)	(0.175)
L.loanstoassets	0.0669	0.852
	(1.295)	(0.955)
L.depositstoassets	-0.412	-0.274
	(0.921)	(0.706)
L.noninterestincomegrossrevenues	0.126	-0.0128
	(0.146)	(0.130)
largest5	1.996	1.127
	(1.754)	(1.080)
Observations	252	394
R-squared	0.370	0.291

Notes: Bank and year fixed effects not shown
Standard errors clustered by country*year.
Banks that failed in 2017 are left out of the sample.
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. Euro Area Banks (Significant Institutions): Key Trends and Stylized Facts 1/

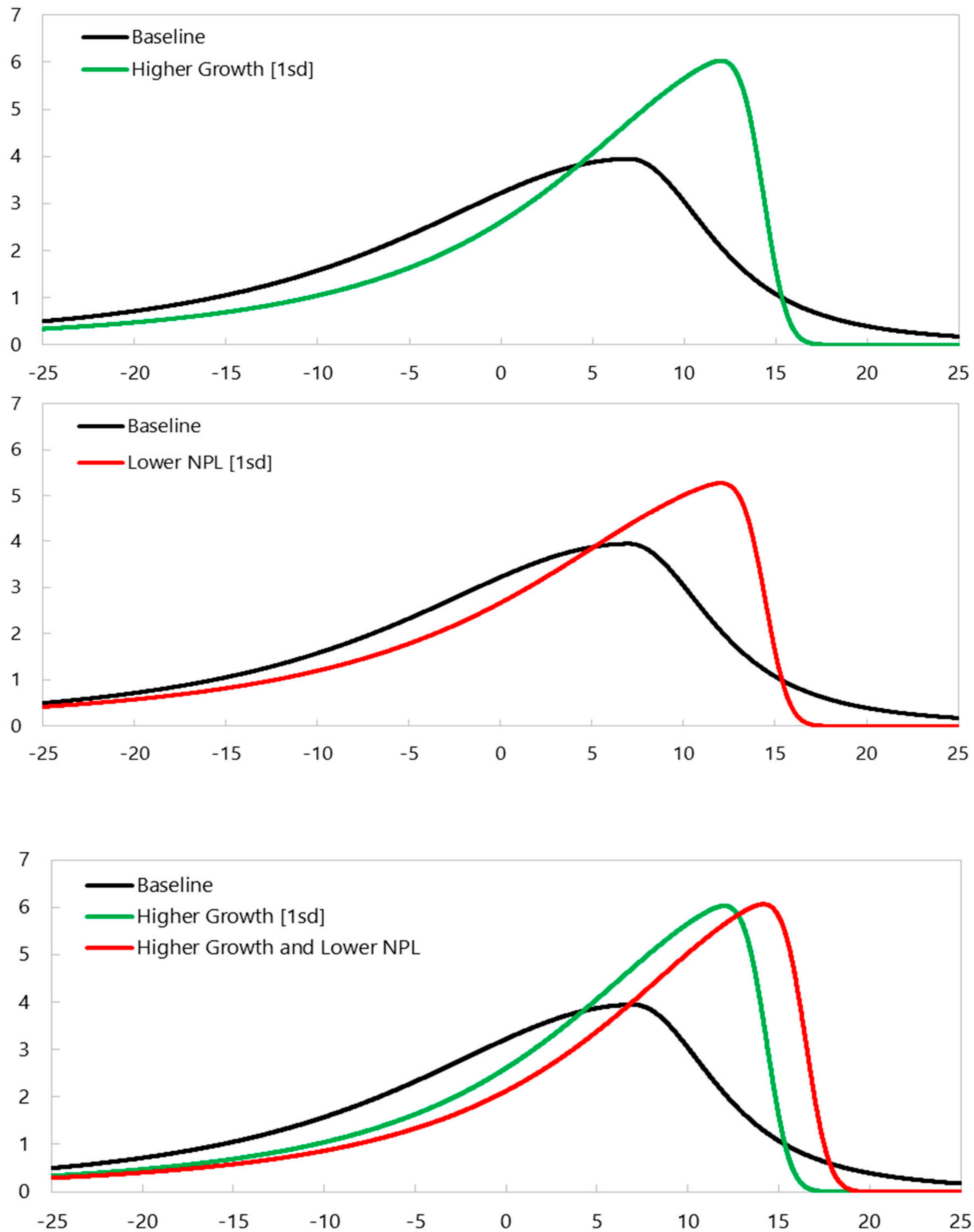


Sources: Bloomberg Finance L.P., Fitch Data, and IMF staff calculations.

1/ Based on a balanced sample of 45 SSM banks over 2007–2016, with 56 percent of end-2016 SSM assets.

2/ Cost of equity estimates, ranging from 8–10 percent, are subject to various caveats including with regards to measurement.

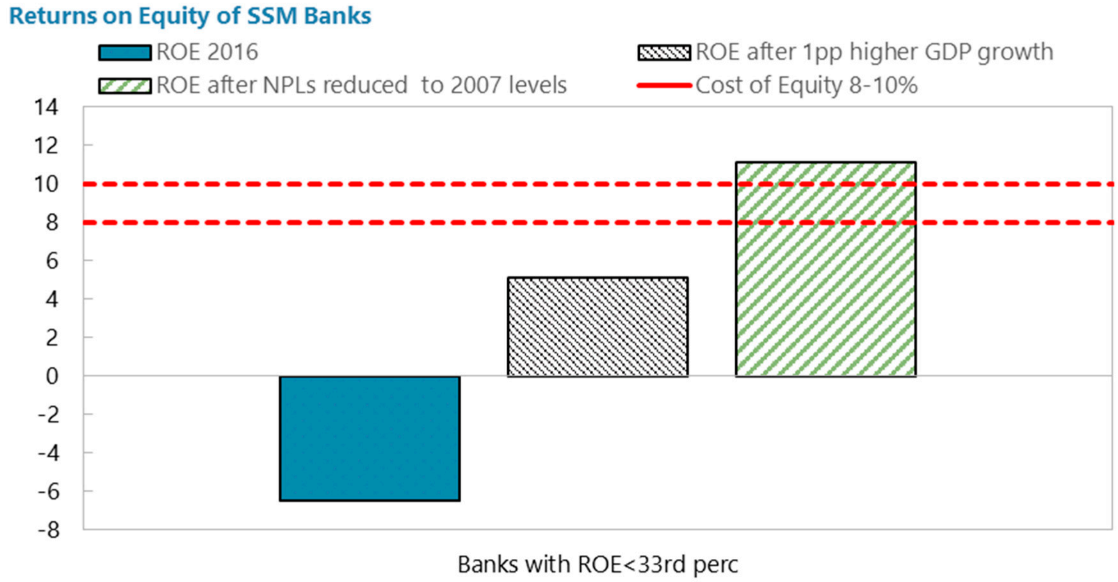
Figure 2. Illustrative Conditional Profitability (ROE) Distributions



Source: IMF staff estimates.

Note: The figure shows illustrative baseline and "shocked" conditional bank ROE probability distributions for a "representative" bank. The distributions are conditional on determinants based on unbalanced quantile regressions for 109 SSM banks over 2007–2016 (which include bank and time fixed effect terms).

Figure 3. Illustrative Exercise: Bank Profitability, Growth, and NPLs



Percentiles of ROE	<33rd percentile
ROE 2016	-6.5
NPLs 2016	18.9
NPLs 2007	3.9
Total Assets (€, trillions)	5.5

Source: Authors' calculations.

Note: The figure is based on Table 10, column 1. "ROE after 1pp higher growth" = ROE 2016 + 11.61*[GDP growth shock=1]. "ROE after NPLs reduced to 2007 levels" = ROE 2016 – 1.178 * [NPL ratio shock = 3.9 – 18.9 = -15].

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BALANCE SHEET-BASED INTERCONNECTEDNESS AND CONTAGION RISK ANALYSIS[27]

46. The assessment of financial system interconnectedness is paramount when appraising systemic risk. This chapter seeks to assess whether the financial system is more likely to absorb or amplify severe shocks originating from within the euro area (EA), from the rest of the EU (including the United Kingdom), or from extra-EU banks or banking systems. In particular, bank exposures are used to quantify contagion risks using two complementary approaches are used: (1) an analysis based on bank-level supervisory records, and (2) country-level analysis over several years.

A. Bank-Level Analysis of Interbank Exposures and Contagion Risk

47. The balance sheet-based analysis in this section focuses on systemic interconnections within and across banking systems. These *direct* (lending and funding) linkages can lead to contagion as shocks spread, and potentially amplified, throughout the financial system, particularly during turbulent market conditions. Network analysis can be used to uncover potentially systemic interlinkages not only within an EA interbank network, but also in an international network that includes individual EA and extra-EA banks.

48. Contagion risks are appraised using Espinosa-Vega and Sole's (2010) network approach applied to granular balance-sheet data on interbank exposures. Supervisory reports on large exposures and on the concentration of funding facilitates the construction of a network which captures the possibility of cascading defaults owing to interbank exposures. The test consists of triggering the hypothetical default of each bank and simulating both credit and funding shocks accounting for the defaulted bank failing on its credit commitments to banking counterparts and causing a liquidity squeeze for banks funded by it. The model tracks the contagion effects in terms of capital losses and the number of banks which experience acute distress when losses exceed banks' capital buffers. An initial shock can propagate for several rounds, triggering cascade effects that can adversely affect banks that were unaffected in the first round. Even in cases without subsequent defaults, the analysis provides estimates for total system-wide losses (contagion index) and individual bank losses (vulnerability index) induced by the network effects of each banks' failure.

49. Interconnectedness analysis focuses on the euro area, but was conducted on a diverse group of banks. Detailed data on large exposures cover 25 large EA banks (at the highest level of consolidation), representing about 55 percent of the area's banking system assets as of June 2017.[28] As discussed earlier, two networks are considered. First, the intra-EA analysis focuses on the interlinkages within this 25-bank sample. Second, the international contagion analysis expands the coverage to include all significant banking counterparts inside and outside the euro area, reaching a

[27] This chapter was prepared by M. Ziya Gorpe (external consultant) and Rohit Goel (Monetary and Capital Markets Department, IMF).

[28] These 25 EA banks represent a subset of those used for solvency and liquidity stress testing. The analysis is based on a very granular bank-level supervisory data for 2017Q2.

total sample size of 154 banks. The 25 EA banks are grouped into three broad business models: (1) G-SIBs, (2) large, but less complex, internationally-active banks, and (3) relatively smaller domestically-oriented banks.

50. In this regard, the analysis builds on the literature in two substantive and interrelated ways: It makes extensive use of supervisory data on large exposures and considers a bank network that goes beyond the EA. For further details on methodology and data, see Appendix I and Appendix II.

Stylized Facts

51. Aggregated bank-level data reveal strong cross-border linkages with non-EA countries and, in particular, those with deep financial sectors.

- Before delving into the granular bank-level analysis, the geographic and sectoral decomposition of the 25 EA banks' asset and liabilities is presented to set the stage with some key stylized facts.
- A heatmap illustrates relative importance of exposures by geography and by sector (Figure 4). While the financial sector has the smallest share (about 6 percent) in the domestic network, linkages with the non-EA financial sectors outweigh almost all other exposures in the table, with a 14 percent share of total assets.
- Decomposing asset exposures further by countries reveals that the top two geographies outside EA are the United States and the United Kingdom. Note that EA banks' exposures to U.K. banks are almost equivalent to their intra-EA bank exposures (Figure 4). On the liabilities side, intra-EA sources provide most of the funding, with the United Kingdom and the United States coming up again as the two largest non-EA geographies (Figure 4). Zooming in on the next set of countries with relatively smaller shares (on the right-hand scales), there is a high degree of overlap (eight out of nine) between the assets and liabilities side.

Figure 4. Euro Area: Banks' Cross-Border Exposures, June 2017

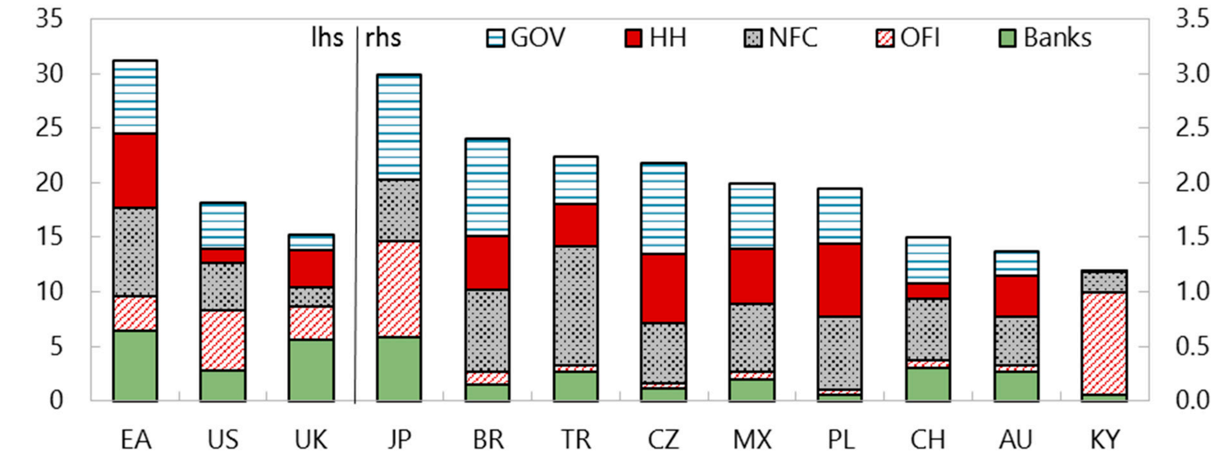
Heatmap of Assets by Orientation and Sector

(in percent of total assets)

	HH	NFC	FIN	GOV	*total*
Domestic	17%	12%	6%	9%	*44%*
Intra-EA	4%	4%	5%	4%	*17%*
RoW	6%	10%	14%	8%	*37%*
total	*26%*	*26%*	*26%*	*21%*	

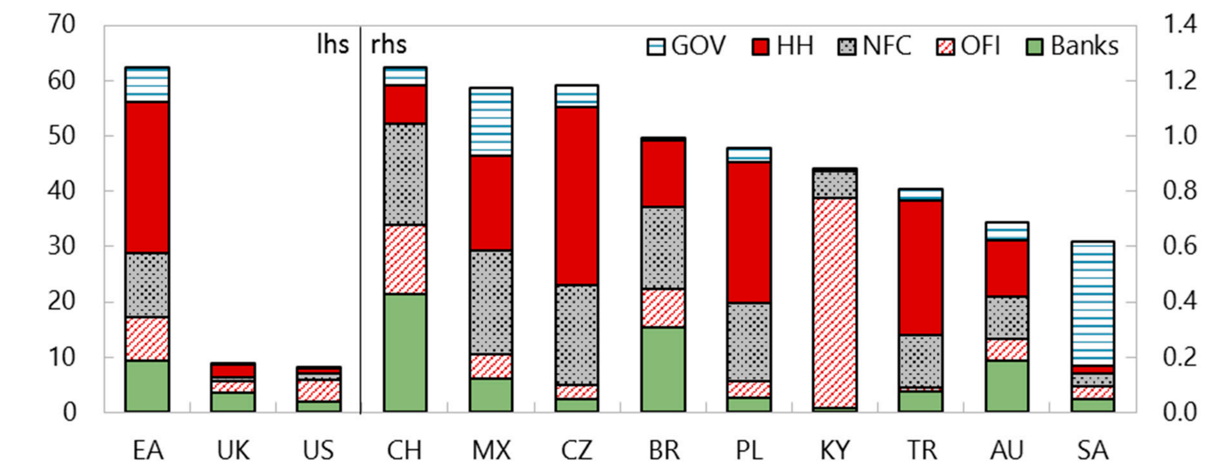
Decomposition of Assets by Counterparty Residence and Sector

(in percent of total cross-border liabilities)



Decomposition of Liabilities by Counterparty Residence and Sector

(in percent of total cross-border liabilities)



Sources: ECB, and IMF staff calculations.

Note: The coverage for this analysis is based on sample banks' FINREP reporting by geography. "Domestic" refers to aggregate domestic (within country) bank exposures, whereas "intra-EA" captures bank exposures to other EA member states.

52. Network representations of the major 25 EA banks' linkages with each other and with the rest of the world visually summarize contagion risks.

- Within the EA interbank system, banks are arranged based on their contagion index (indicated by node size) and clustered together based on the strength of their bilateral connections (indicated by line thickness) (Figure 5).[29] They are then distinguished by colors based on business models. The within EA interbank network indicates that G-SIBs play a central role and are the main potential source of contagion for the domestically-oriented banks.

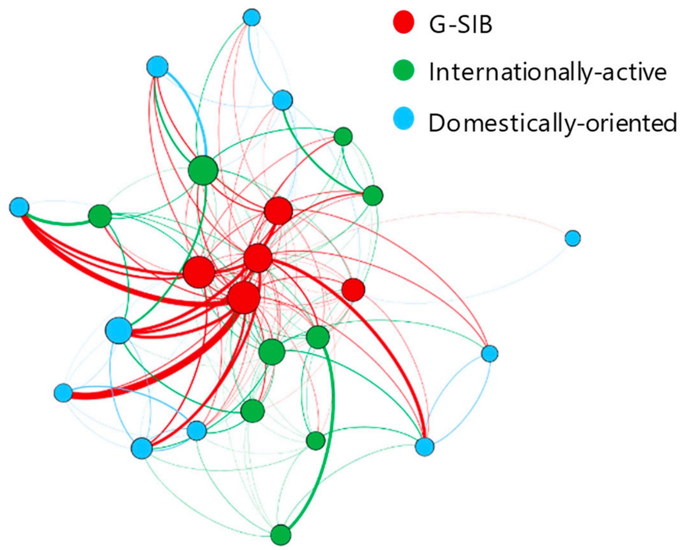
- For the global network, node size and line thickness indicate a bank's contagion level and strength of its bilateral connections, respectively. However, banks are selectively arranged with the 25 EA banks in the inner circle and their counterparts in the outer circle clustered together by regions. Colors are used to distinguish regional groups from each other except for G-SIBs, which are uniformly indicated by black nodes. The prevalence of the thicker lines between the inner and outer circles in the global network suggests that EA banks' cross-border linkages dominate their intra-EA connections (Figure 5). Furthermore, this network depiction highlights the inward spillovers to non-G-SIB EA banks (red nodes in the inner circle) from global G-SIBs (black nodes in the outer circle), which are mainly located in the rest of the EU and other advanced economies (AE).

[29] Intra-EA network graph uses a force-directed algorithm (Hu, 2005) to determine spatial relationships between the banks based on the strength of exposures and density of connections. In this visualization algorithm, the length between two banks is determined by exposure-to-capital buffer ratio to cluster highly connected banks together, and the forces between two different banks are determined by their contagiousness for spatial arrangement that places systemic entities in the center.

Figure 5. Euro Area: Network Graphs, June 2017

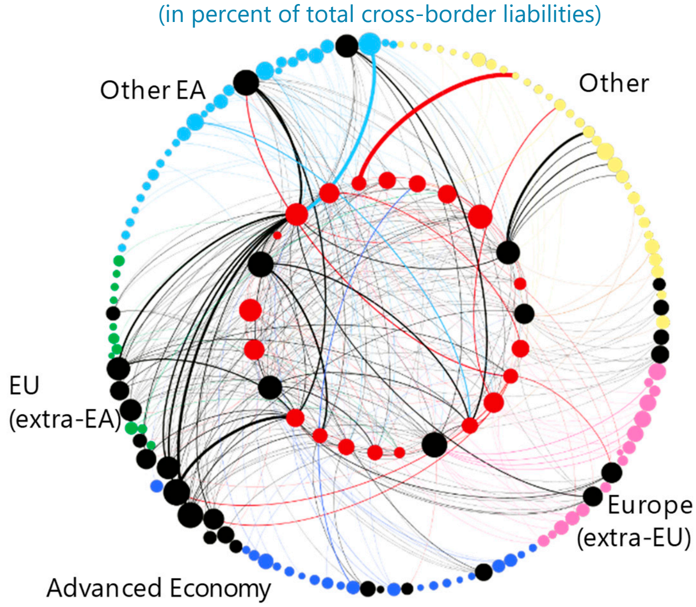
Intra-EA Network

(in percent of capital buffer)



EA-centric Global Network

(in percent of total cross-border liabilities)



Sources: ECB, and IMF staff calculations.

Note: Top panel: The 25 euro area banks are grouped into three broad business models: (1) G-SIBs (red nodes), (2) large, but less complex, internationally-active banks (green nodes), and (3) relatively smaller domestically-oriented banks (blue nodes). Node size represents the strength of contagion; node color indicates business model; line thickness is proportional to the ratio of exposures to capital buffer; line color is the same color as the contagion source.

Bottom panel: Banks are grouped by regions: EA (25 banks), other EA, EU (extra-EA), Europe (extra-EU), (other) Advanced Economies, and Other. Inner circle comprises 25 EA banks with their important banking counterparts placed in the outer circle, grouped into regions denoted by different colors. Node size: contagion index; line color: matches the color of the source of contagion (indicates direction); edge size; exposure-to-capital ratio; G-SIBs are indicated in black. See Appendix II for the list of countries in each group.

Appraisal of Contagion Risks

53. The analysis reveals that contagion risks stemming from intra-EA banking exposures are at present moderate. This is because interbank exposures are modest relative to banks' capitalization (based on 2017Q2 data). In the main adverse scenario, no hypothetical default of a single bank would cause acute distress to another bank, and thus there are no cascade effects.

- The entity with the highest contagion index causes system-wide losses of around 11 percent in relation to sum of its counterparties' capital buffers (Figure 6). This is appreciably greater than an average index reading of 2.6. As for the decomposition of shocks, about 7 percent in system-wide losses can be attributed to the bank defaulting on its credit commitments while the remaining 4 percent to it withdrawing funding. More generally, the results suggest that contagion appears to spread more virulently through credit rather than funding shocks.

- The most vulnerable entity incurs losses of less than 7 percent of its capital, which is mostly accounted for by credit shocks (Figure 6). In the case of vulnerability, banks are comparatively more evenly dispersed around the index average of 2.8.

- Therefore, within this closed network, although one bank is a key transmitter of shocks, the diffusion of contagion is not concentrated.

- The analysis by business models confirms the visual clues from the intra-EA network graph. G-SIBs are by far the main source of contagion and, on the receiving end, domestically-oriented banks score slightly above the other groups in terms of vulnerability, mostly driven by the credit shock (Figure 6).

54. Cross-border contagion analysis points to a relatively stronger propagation of shocks originating in advanced economy banks. However, these risks appear to be generally manageable based on 2017Q2 data. Decomposing the spillover indices by regions facilitates the comparison of intra-EA contagion with cross-border contagion risks. Banks are grouped according to the following regions: EA (25 banks), other EA, EU (extra-EA), Europe (extra-EU), (other) AE, and Other (Figure 7).

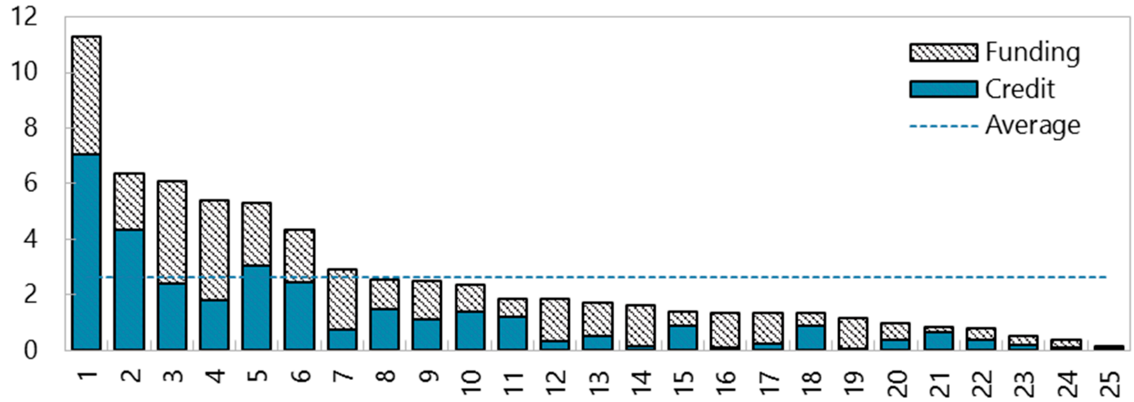
- Figure 7 shows the breakdown of each bank's outward spillovers (or contagion) by regions. For example, about half of contagion associated with the first (EA25) bank is transmitted to the EA. Outside of the EA, this bank's spillovers are most notable for the extra-EU European banks. More generally, advanced economy banks are the main recipients of cross-border contagion from the 25 EA banks in focus.

- The vulnerability of EA banks become markedly concentrated when their cross-border exposures are considered. For instance, the vulnerability indices of three banks are quite high compared to the rest (Figure 7). More generally, banks from advanced economies play a relatively important role in spreading distress to the EA banks. In the global network, the vulnerability of the 25 EA banks to intra-EA contagion is notably less than cross-border spillovers.

Figure 6. Euro Area: Intra-EA Interconnectedness Analysis, June 2017

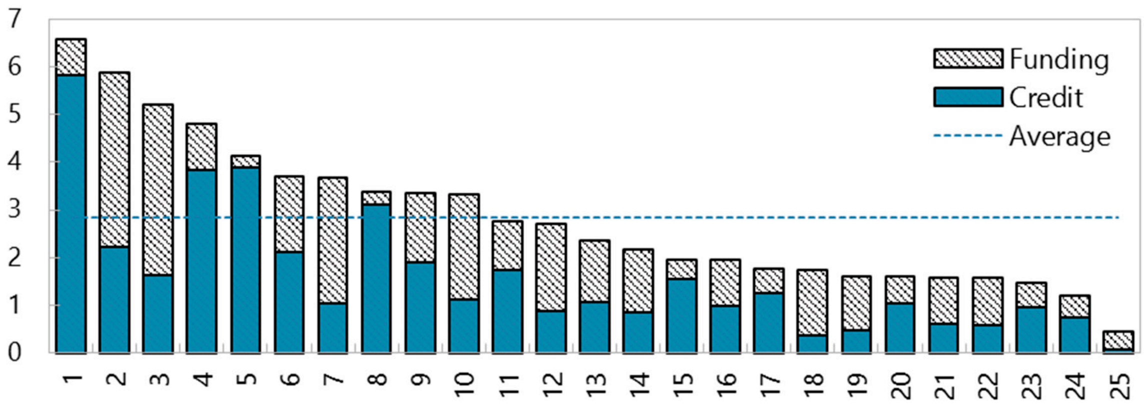
Contagion: Outward Spillovers by Type of Shock

(losses in percent of capital buffer)



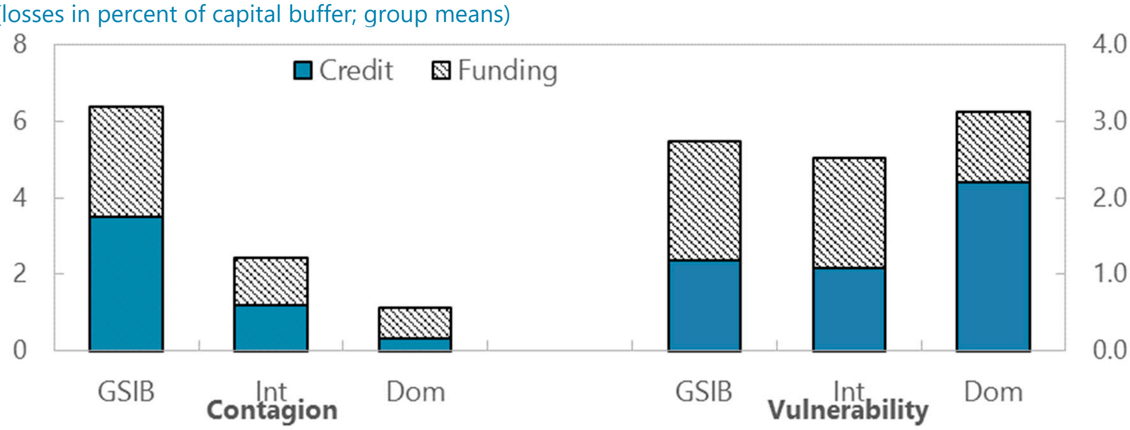
Vulnerability: Inward Spillovers by Type of Shock

(losses in percent of capital buffer)



Outward and Inward Spillovers by Business Model

(losses in percent of capital buffer; group means)



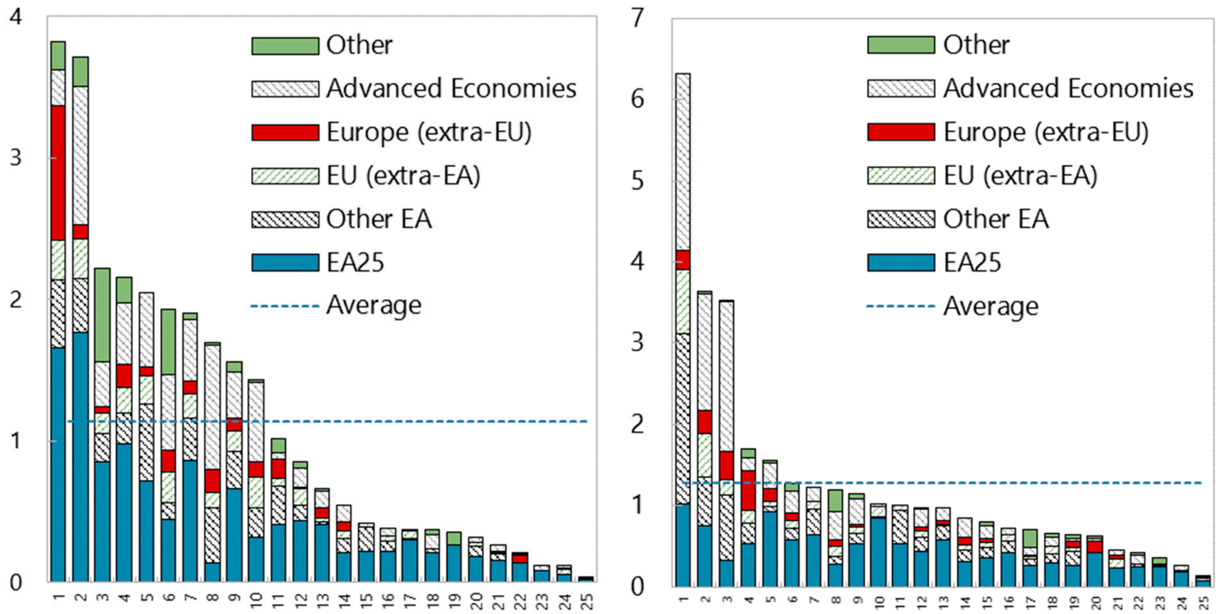
Sources: ECB, and IMF staff calculations.

Note: The bank labels only reflect the ranking on the respective chart. For example, the hypothetical default of the most contagious bank, Bank 1, results in the average losses to the other 24 banks of around 11 percent of their capital buffer. The most vulnerable bank, also labeled Bank 1, incurs average losses of about 6.5 percent of its capital buffer across 24 independent simulations. The results are based on the main adverse scenario with: λ=60 percent (loss given default); ρ=50 percent (funding shortfall); and 50 percent discount rate for fire sales. Furthermore, it is assumed that a decline of 5 percent of RWA in CET1 would cause acute distress to an exposed bank.

Figure 7. Euro Area: Cross-border Contagion Analysis, June 2017

Contagion: Outward Spillovers by Regional Grouping
(losses in percent of capital buffer)

Vulnerability: Inward Spillovers by Regional Grouping
(losses in percent of capital buffer)



Sources: ECB, and IMF staff calculations.

Note: The bank labels only reflect the ranking on the respective chart. For example, the hypothetical default of the most contagious bank, Bank 1, results in the average losses to the other 153 banks of close to 4 percent of their capital buffer. The most vulnerable bank, also labeled Bank 1, incurs average losses of about 6.5 percent of its capital buffer across 153 independent simulations. The results are based on the main adverse scenario with: λ=60 percent (loss given default); ρ=50 percent (funding shortfall); and 50 percent discount rate for fire sales. Furthermore, it is assumed that a decline of 5 percent of RWA in CET1 would cause acute distress to an exposed bank.

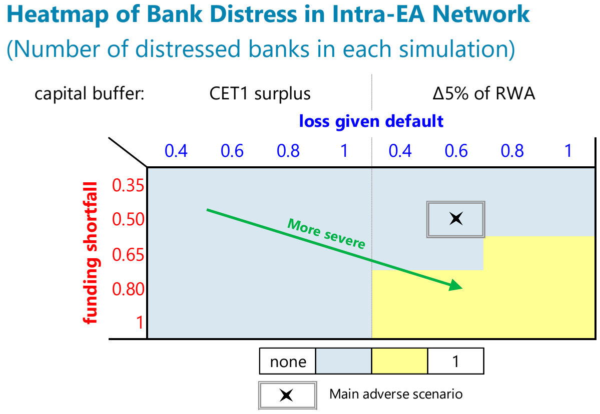
Robustness Analysis

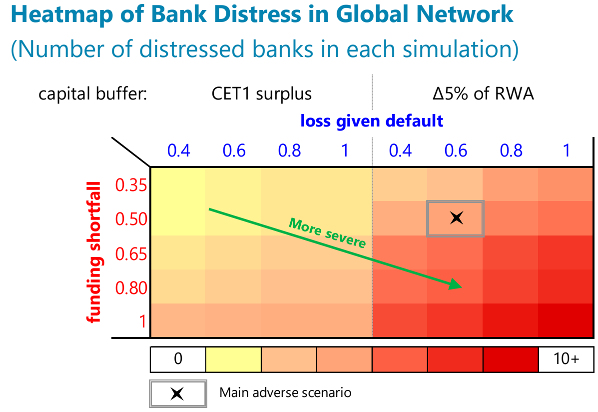
55. A wider range of parameters were used as sensitivity checks. The model assumptions in the main adverse scenario simulate a moderately severe shock.

- Even under more extreme assumptions applied to intra-EA network, only one bank faces acute distress, reaffirming the resilience to interbank contagion (Figure 8).

- In contrast, the larger global cross-border network is more sensitive to changes in model parameters and assumptions (Figure 8). If a less conservative capital buffer were to be used, allowing for the entire CET1 surplus to be depleted before an acute distress occurs, the number of distressed banks would remain limited (occurring in a single round) even under more extreme calibrations. However, increasing the loss given default parameter from 60 percent to 80 percent and raising funding shortfall ratio from 50 percent to 65 percent, which are significantly harsher assumptions, leads to more than twice the number of acute distresses in the global network.

Figure 8. Euro Area: Bank Distress Sensitivity to Model Assumptions





Sources: ECB, and IMF staff calculations.

B. Country-Level Analysis of Cross-Border Linkages and Contagion Risk

This section provides a complementary and dynamic appraisal of contagion risks using country-level data. In particular, an international interbank network based on countries' most material exposures is constructed for selected years. The focus of the analysis is the interconnectedness of the euro area banking system with banking systems in other regions. After documenting key stylized facts, analysis based on Espinosa-Vega and Sole (2010) is used to assess how acute distress in one banking system spills over to other regions.

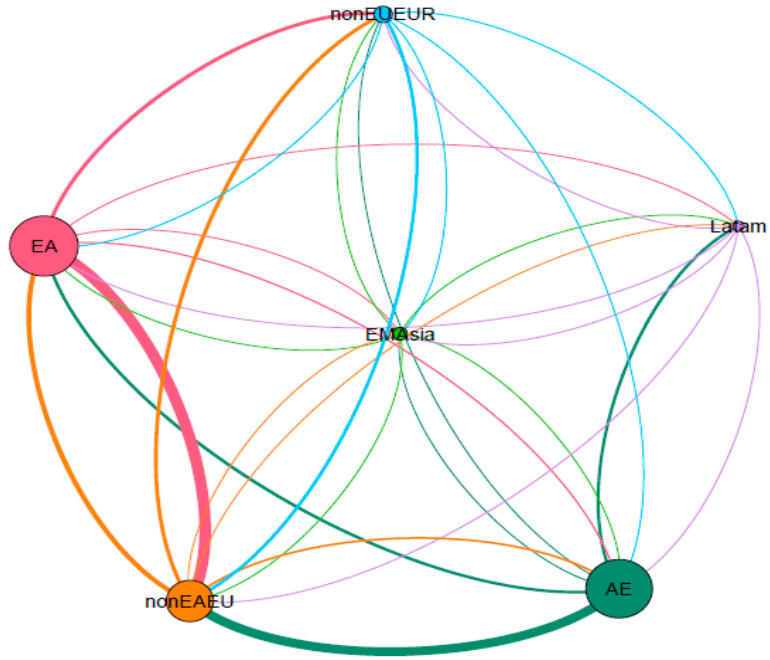
56. The euro area is most strongly connected to non-euro area European Union (EU) countries (Figure 9). The connections reflect both lending- and funding-based intermediation, which correspond to outward and inward exposures, respectively. Extra-EU European exposures with other regions are limited.

57. The euro area banking system's cross-border linkages have declined over time. On one hand, international lending by euro area banks has generally decreased, partly reflecting the continuing consolidation of the area's banking system (Figure 9). Likewise, funding exposures have also diminished (Figure 9). In both cases, the declines are more pronounced vis-à-vis EU countries outside of the euro area. At the same time, there is a marginal rise in recent years in exposures to euro area from (non-European) advanced and emerging market economies as well as extra-EU countries, possibly owing to the global expansion by non-euro area banks to euro area

Figure 9. Global Interbank Exposure

The euro area (EA) is most strongly connected with non-euro area European Union countries

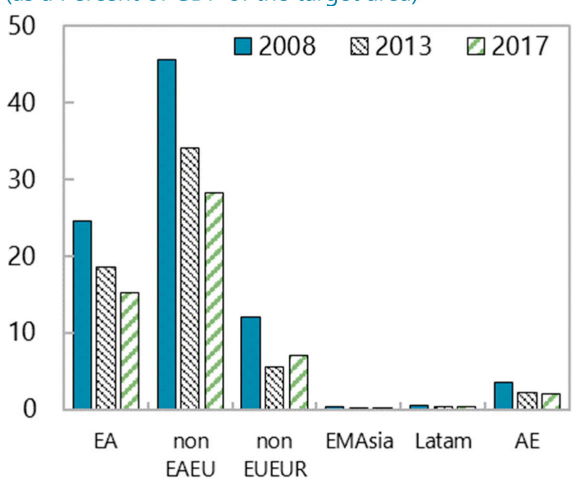
Global Interbank Exposure
(index)



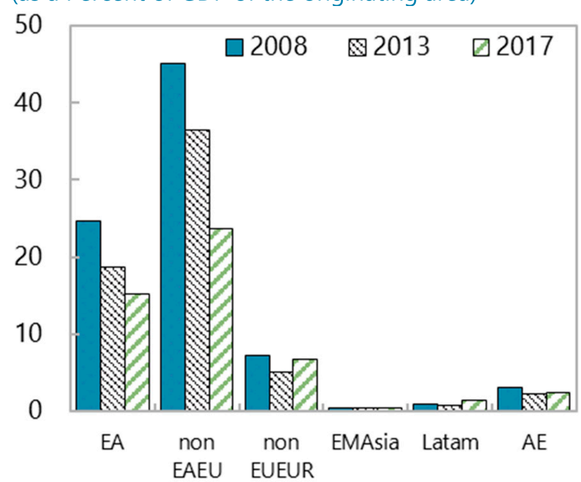
Exposures from EA have reduced sharply, in particular within the EU.

Exposures to EA have reduced from within EU, but marginally picked up elsewhere.

Exposure from Euro Area
(as a Percent of GDP of the target area)



Exposure to the Euro Area
(as a Percent of GDP of the originating area)



Sources: Bank for International Settlements, FSI, Country authorities, and IMF staff estimates.

Note: In panel 1, dots represent the various regions and lines represent the exposures between the two regions. Color of the lines is that of the source, so the color shows the direction of the exposure. Thickness of the lines represent the exposures between the two regions as a proportion of the capital of the recipient region. Thickness of the dots represent the total outward exposures. The data comprises 55 jurisdictions, which are divided into key regions including euro area (EA), non-EA European Union (nonEAEU), non-EU Europe (nonEUEUR), EM Asia, Latam, and Other Advanced Economies (AE).

Spillover Risks To and From the Euro Area Banking System

58. Advanced economies remain most critical for analyzing the spillover risks for euro area banking systems:

- The analysis reveals that acute euro area banking distress affects EU banking systems to the greatest extent, while emerging and other advanced economies are less impacted (Figure 10). The bars reflect the average contagion impact to the regions, originating from euro area credit and funding distress. Compared to 2013, the contagion impact has moderated for the advanced economies, but has edged up in the emerging economies reflecting the evolving exposure patterns discussed earlier.

- The results also indicate that the euro area banking system is most prone to banking distress emanating from non-European advanced economies and from within the EU banking systems (Figure 10). This vulnerability has declined over the last few years. The analysis also suggests that contagion risks can persist for multiple cascading rounds highlighting the importance of indirect exposures particularly from larger geographies.

Figure 10. How is Euro Area Connected to Key Global Nodes?

Potential shocks from the euro area (EA) are likely to most impact the non-EA EU and EA regions.

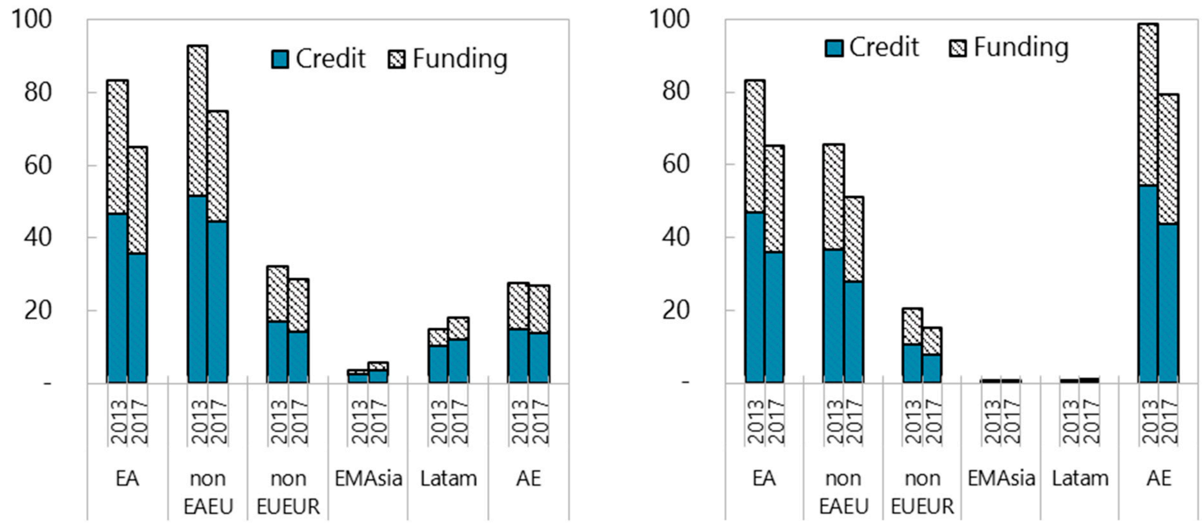
Index of Contagion for EA

(index)

EA is most vulnerable to shocks from advanced economies (excluding Europe) followed by from within EA.

Index of Vulnerability of EA

(index)



Sources: Bank for International Settlements, FSI, Country authorities, Espinosa-Vega and Sole (2010), and IMF staff estimates.

Note: The index of contagion for EA represents the average loss experienced by each region (expressed as a percentage of their core capital) due to the triggered failure of one country within the EA (this indicates how a banking failure in EA impacts the other regions). The index of vulnerability of EA represents the average loss experienced by the Euro Area region (expressed as a percentage of the core capital) across individually triggered failures of all other countries within the respective regions. (this indicates how is EA impacted by a banking failure in other regions). Index for a region is calculated by the taking the average of the indices across all the respective constituent countries. Regions: nonEAEU: Non-EA European Union (EU); nonEUEUR: Non-EU Europe; EMAsia: Emering Asia; Latam: Latin America; AE: Other Advanced Economies.

Robustness Analysis

59. The findings are broadly robust to alternative model calibrations (Figure 11). The model assumptions in the baseline scenario simulate a scenario to capture the impacts of an extreme credit and funding shock.[30] A wide range of credit shocks were tested as a sensitivity check on the baseline simulation. While the model outputs—such as the contagion and vulnerability indices—change with the model parameters and assumptions, the relative systemic importance of the regions remain unchanged.

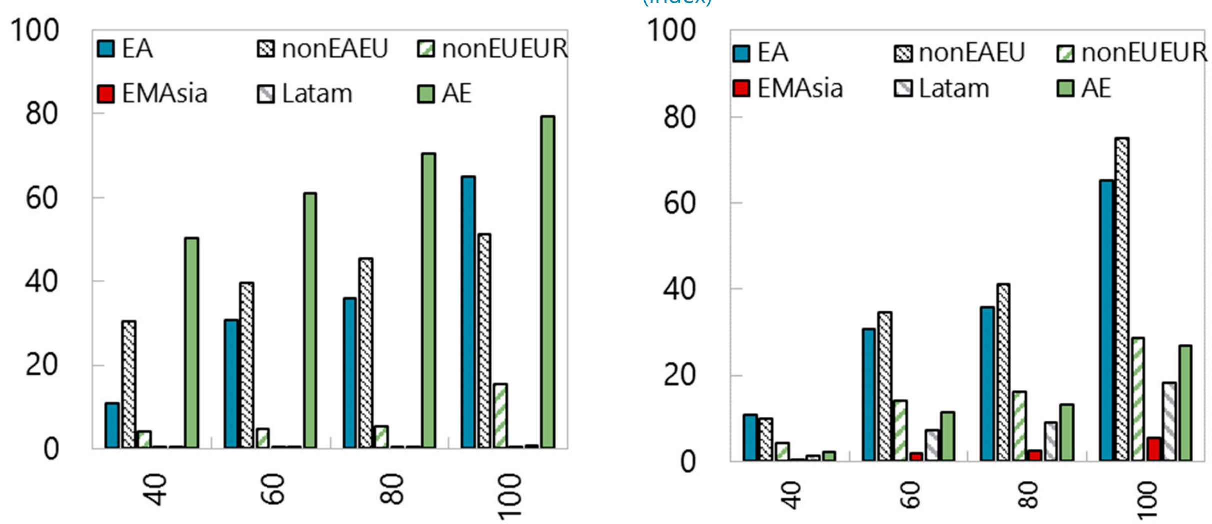
Figure 11. Sensitivity of the Results to the Various Loss-Given-Default Parameters

All factors are sensitive to the assumption, but the order remains the same.

Index of Contagion
(index)

The index from within EA is highly sensitive to the assumption, but remains high throughout for the other AEs.

Index of Vulnerability
(index)



Sources: Bank for International Settlements, FSI, Country authorities, Espinosa-Sole (2010), and IMF staff estimates.

Note: The x-axis highlights the various assumptions for the loss-given-default in the credit shock scenario.

C. Caveats

60. The network analysis is subject to potential misestimation of contagion risks owing to a number of caveats:

- On the modeling side, other than the extreme nature of the initial shock (outright hypothetical failure of a bank), the Espinosa-Vega and Sole (2010) framework focuses on identifying spillovers

[30] A loss given default rate of 100 percent is also assumed in Espinoza-Vega and Sole (2010), the Germany 2016 FSAP, the Italy 2013 FSAP, and the Japan 2012 FSAP. Espinoza-Vega and Sole (2010) and Wells (2004) argue that network studies should consider higher loss-given-default estimates than typically assumed, as banks tend to face substantial uncertainty over recovery rates in the short run. The simulation results should be interpreted as the maximum possible impact of systemic instability. Note that collaterals and hedging instruments are not considered due to data limitations.

via direct bilateral exposures between banks and, as a result, fails to incorporate market perceptions to exposures. For example, the contagion could spread faster and wider if the model considered additional losses due to common exposures. Furthermore, this is a static model with simplifying assumptions on how credit and funding shock loses are absorbed by bank capital (e.g., no liquidation pecking order, no re-optimization by banks).

- On the data side, a key limitation is that the bank-level analysis is based on a single point in time (2017Q2). Limited counterparty-level data on funding sources only allow for partial analysis of spillovers vis-à-vis non-EA banks. Although it has benefits, using consolidated reporting leads to loss of information on more complex network relationships. In particular, the analysis neglects the spread of contagion due to subsidiary-parent linkages.[31] The country-level analysis provides a dynamic perspective on how contagion risks evolve, yet the use of locational reporting data, notwithstanding its benefits, also overlooks potentially important network connections. The change in contagion and vulnerability risks, at a country level, captures the change in exposures, and does not account for a change in the underlying capital levels owing to data limitations.

D. Summary and Policy Implications

61. Taken together, the results suggest that the risk of contagion through EA interbank exposures are currently modest relative to extra-EA exposures. Network analysis suggests that major EA bank capitalization levels are sizeable relative to the degree of their interbank connectedness. However, cross-border linkages, including with other European and U.S. banks, are relatively stronger. Within the EA network, G-SIBs tend to be associated with higher contagion index scores, while more domestically-oriented banks register higher vulnerability index scores in response to simulated acute banking distress. The global banking network indicates that spillovers are greatest between the euro area and other advanced economies (including those in Europe). Country-level analysis is consistent with these results and also indicates that EA spillovers have been decreasing in recent years, in parallel with the downward trend in exposures with other regions.

62. Several recommendations follow from the analysis: Data gaps on bilateral exposures should be closed and data standards across euro area jurisdictions need to be further harmonized. The lack of harmonization on counterparty identification across national jurisdictions can obscure legal and economic connections, and thereby impede the timely monitoring of risks. Although large exposure reporting provides a detailed breakdown of assets at the counterparty-level, the information on bilateral liability positions is still limited to the ten largest funding sources (concentration of funding). Expanding the scope beyond a limited subset of counterparties with a breakdown by product types would enrich the appraisal of systemic vulnerabilities. The framework for assessing interconnectedness—already very sophisticated in many aspects—could be enhanced by more extensively utilizing large exposure databases and by expanding the network coverage to better capture spillovers vis-à-vis non-EA entities.

[31] Contagion risk emanating from foreign parents to Luxembourg-domiciled subsidiaries, reflecting large intra-group exposures, was highlighted in the context of Luxembourg 2017 FSAP (IMF, 2017).

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Espinosa-Vega, Marco, and Julian Solé (2010), "Cross-border Financial Surveillance: A Network Perspective," *IMF Working Paper* No. 105, April.

International Monetary Fund, 2017, "Technical Note – Risk Analysis," Luxembourg Financial Sector Assessment Program, IMF Country Report No. 17/261, August 2017, Washington D.C.

Hu, Y. F. (2005), "Efficient and high-quality force-directed graph drawing," The Mathematica Journal, 10 (37–71).

Appendix I. Euro Area: Stress Test Matrix (STeM) for the Banking Sector: Contagion Risks

Domain		Assumptions
		Top-down by FSAP Team
Banking Sector: Contagion Risk		
1. Institutional Perimeter	Institutions included	• 25 banks
	Market share	• 55 percent of total EA banking system assets (consolidated)
	Data and baseline date	• Latest data: June 2017 • Source: supervisory data (COREP, LE, AMM) • Scope of consolidation: highest level of consolidation within EA
2. Channels of Risk Propagation	Methodology	• Balance sheet-based financial metrics • Bank network model by Espinosa-Vega and Solé (2010) with credit and funding shocks
3. Tail shocks	Size of the shock	• Pure contagion: default of institutions
4. Reporting Format for Results	Output presentation	• Number of undercapitalized institutions in distress, and their shares of assets in the system • Cascade effects, and direction and size of spillovers within the network
Country level analysis: Contagion Risk		
1. Institutional Perimeter	Institutions Included	• Total of 208 countries divided into key regions: Euro Area, non-EA European Union, non-EU Europe, EM Asia, Latam, Other Advanced Economies and Rest of the world
	Data and baseline date	• Latest data: 2017 Q1 (Historical snapshots for 2008 and 2013) • Source: BIS • Scope of consolidation: Consolidation is done on a locational and residence basis
2. Channels of Risk Propagation	Methodology	• Balance sheet-based financial metrics • Bank network model by Espinosa-Vega and Solé (2010) with credit and funding shocks
3. Tail shocks	Size of the shock	• Pure contagion: default of institutions
4. Reporting Format for Results	Output presentation	• Proportion of capital under distress, and direction and size of spillovers within the network

Appendix II. Methodology, Data, and Implementation

This appendix provides and overview and the methodology used to quantify contagion risks as well as further information on data and implementation.

Methodology

The balance sheet-based network analysis follows Espinoza-Vega and Sole (2010) framework to simulate the default of one bank at a time and to track how the contagion spreads to the rest of the network. This approach not only considers contagion through direct bilateral connections, but also indirectly through third parties by accounting for potential "cascade effects" after the initial round of distress in the network. Cascade effects continue until there is no more subsequent failures in the network. The model looks at both credit and funding channels of the contagion from a given bank. To analyze the effects of a credit shock, the exercise simulates the individual default of each bank (with probability of default=1), for a given loss-given-default parameter (λ), where the counterparties' capitals absorb the losses on impact. Then, bank i is said to experience acute distress if its capital buffer is insufficient to fully cover its losses due to bank h defaulting:

- that is if $k_i - \lambda x_{hi} < 0$, where x_{hi} stands for bank i loans to bank h and k_i stands for i's capital buffer.

As for the funding shock, in this stylized exercise, it is assumed that banks are unable to replace all the funding previously granted by the defaulting bank, which, in turn, triggers a fire sale of assets. In this setup, bank i is able to replace only a fraction (1-ρ) of the lost funding from bank h, and its assets trade at a discount, so that bank i is forced to sell assets worth $(1+\delta)\ \rho x_{ih}$ in book value terms, where x_{ih} stands for bank i borrowing from bank h. The funding shortfall induced loss, $\delta\rho x_{ih}$ is absorbed by bank i's capital. Then, bank i is said to experience acute distress if its capital buffer is insufficient to fully cover the funding shortfall induced loss due to bank h defaulting:

- that is if $k_i - \delta\rho x_{ih} < 0$.

When the credit and funding shocks are combined, the condition causing acute distress can be formulated as:

- $k_i - (\lambda x_{hi} + \delta\rho x_{ih}) < 0$.

In the subsequent rounds, if there are new banks experiencing acute distress, the losses need to be accumulated over all the rounds in order to test the inequalities above.
In terms of results, this exercise generates four main outputs for each bank (bank i):

a) Induced failures: the number of subsequent system-wide failures if bank i fails first;

b) Vulnerability level: total number of independent simulations (one per each bank's failure) under which bank i falls into distress as a consequence;

c) Index of contagion: averages the percentage of loss of other banks due to the failure of bank i:

- Contagion index of bank i: $\mathrm{CI_i} = 100 * \sum_{j \neq i} L_{ji} / \sum_{j \neq i} K_j$

where K_j is bank j's capital and L_{ji} is the loss to bank j due to the default of bank i.

d) Index of vulnerability: averages the percentage of loss of bank i due to the failure of all other banks:

- Vulnerability index for bank i: $\mathrm{VI_i} = 100 * \sum_{j \neq i} L_{ij} / (n-1) * K_i$

where K_i is bank i's capital, L_{ij} is the loss to bank i due to the default of bank j, and n is the number of banks in the network.

The main adverse scenario in this exercise assumes λ=0.6, ρ=0.5, δ=1, which means that loss-given-default is 60 percent, the fraction of funding shortfall is equal to 50 percent with a 50 percent discount rate on the assets that a bank may be forced to sell. This can be described as a moderately severe shock scenario to stress-test the banking system from the perspective of contagion risk. Since the credit risk mitigation measures amount to 15 percent of gross exposures, and all remaining exposures can be assumed to be at risk in the case of a default, 60 percent loss given default assumption is suitable for a moderately severe scenario. Given the challenges in calibrating the other parameters based on actual data, assumptions similar to those considered in previous FSAPs were used to simulate an adverse scenario and a wide range of sensitivity checks were conducted.

Bank-Level Data

The data on interbank exposures and Tier 1 capital can be obtained from COREP templates.
The two main supervisory data sources are:

- *COREP Large Exposures* template shows the breakdown of each bank's assets by counterparty. A large exposure is defined as an exposure that is 10 percent or more of a bank's eligible capital base vis-à-vis a single borrower or a group of connected clients. For qualifying exposures vis-à-vis a group of connected clients, all exposures vis-à-vis each client in the group must be reported regardless of the 10 percent threshold. For the network analysis, a comprehensive dataset was built by combining the data reported by each bank in the sample. Due to the dataset size as well as the imperfect nature of the reported metadata, the biggest task involved reconciling all the counterparty level data into a standard form where the counterparties as reported by different banks could be matched and further filtering can be performed. Large exposures data was used to fill blocks A and B on Appendix II Figure 1.

- *COREP Concentration of Funding by Counterparty (C 67.00)* template reports the top ten largest counterparties either as a single creditor or a group of connected clients from which funding obtained exceeds a threshold of 1 percent of total liabilities. In order to expand the scope beyond EA banks, large exposures reporting on the asset side was complemented with largest funding sources on the liabilities side of banks' balance sheets. Completing the funding dataset was relatively less complex task as the data reported on the top ten largest counterparties by its nature is limited to a small number of counterparties and metadata reporting is of higher quality. Data from this template was used to fill block C in Appendix II Figure 1. Because of the limited nature of the data on the funding sources, analysis that relies on block C can only provide a partial picture and the resulting conclusions can only underestimate the associated spillovers.

Country-Level Data

The country-level analysis comprises 208 jurisdictions. These are then divided into key regions including Euro Area (EA), non-EA European Union (nonEAEU), non-EU Europe (nonEUEUR), EM Asia, Latam, Other Advanced Economies (AE), and Rest of the world (ROW). The focus is on the first six clusters which capture the majority of the exposures and have reliable aggregate data. The index for each cluster is taken as an average of the constituent countries. The analysis is based on 2008Q4, 2013Q1 and 2017Q1.

Cross-border banking exposure claims data are based on BIS locational banking statistics on a residence basis. For those countries, which do not report the exposure claims data directly, a partial map is created using the cross-border banking exposure liabilities. Core capital data are taken from IMF's FSI Statistics and central bank authorities. Some countries where country level country data is not available are assumed to have a high capital level so that they never fail under the simulations. Most of these countries are relatively smaller in size, and most likely do not impact the final outcome of the analysis.

Implementation

Contagion analysis relied on Espinosa-Vega and Sole methodology for the analysis of supervisory data on banks' large exposures and funding sources provided in a secure room at the ECB.

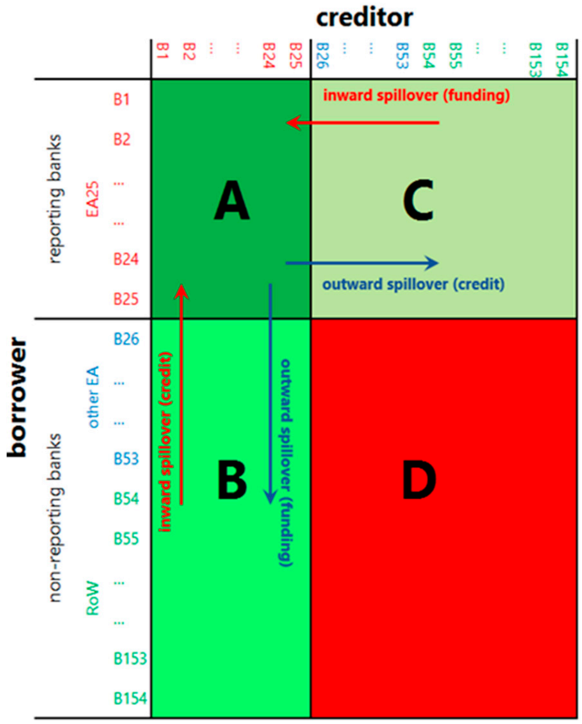
- For the intra-EA analysis, the initial data collection focused on the main 25-bank sample, where a 25 by 25 matrix was constructed (block A on Appendix II Figure 1) amounting to a total of €125 billion.
- For the international contagion analysis, the 25-bank sample was expanded to incorporate significant counterparties within EA and outside. The large exposure data was complemented with the 10 largest counterparties who provide funding. The scope of the network is contained to the counterparties classified as credit institutions. Furthermore, in order to have a consistent sample, all the individual counterparty level data was aggregated to the level bank holding groups to the extent possible but excluding exposures to nonbanking clients within each group. The exposures vis-à-vis clients amounting to less than €100 million were filtered out. After the aggregation and filtering, the final network dataset comprised: (i) the 25 EA reporting banks;

(ii) 28 additional banks in EA (not part of the main sample); (iii) 101 banks outside EA. The global network including intra-EA exposures total to about €524 billion.

- The data collection focused on gross exposures after deducting exemptions but before credit risk mitigation measures given limited information and resources to analyze underlying collateral for each counterparty. While this is a limiting factor, overall credit risk mitigation measures (substitution effect and funded credit protection) amount to about 15 percent of gross exposures between banks and the exercise tests a wide range of loss-given-default ratios as a sensitivity check.
- Two different assumptions were considered with respect to capital buffer in this exercise: one that allows banks to deplete all their CET1 surplus (CET1 in excess of the minimum 4.5 percent) before an acute distress occurs, and a narrower buffer, where a decline in CET1 corresponding to 5 percentage points of risk-weighted assets would cause an acute distress in a bank. For all non-reporting banks, only the Tier 1 measure was available publicly. The average ratios of these two buffers in relation to full CET1 (0.67 and 0.33, respectively) for reporting banks were applied to Tier 1 capital of non-reporting banks to approximate their buffers based on proportionality.
- Regional categories are used to decompose the spillover indices on a geographical basis. Quantifying the contribution of each group to these indices facilitates a broad comparison between the results from intra-EA analysis and those from the global network analysis. Increasing the number of banks in the network generally causes a downward bias on the indices due to averaging. Hence, the index values alone do not serve as suitable measures for comparing networks of different sizes, namely the intra-EA network versus the global network. However, the contribution of EA25 group to the overall index values can serve as a basis to compare the contributions from other groups in the global network. The regional categories are formed as follows: EA25: member states of the euro area where the 25 reporting banks are located; Other EA: member states of the euro area where the other, non-reporting banks are located; EU (extra-EA): Denmark, Poland, Sweden, United Kingdom; Europe (extra-EU): Norway, Russia, Switzerland, Turkey; Advanced Economy: Australia, Canada, Japan, Korea, Singapore, United States; and Other: Algeria, Azerbaijan, Brazil, Chile, China, Egypt, Hong Kong, India, Mexico, Morocco, Qatar, Thailand, Tunisia, United Arab Emirates, Vietnam.

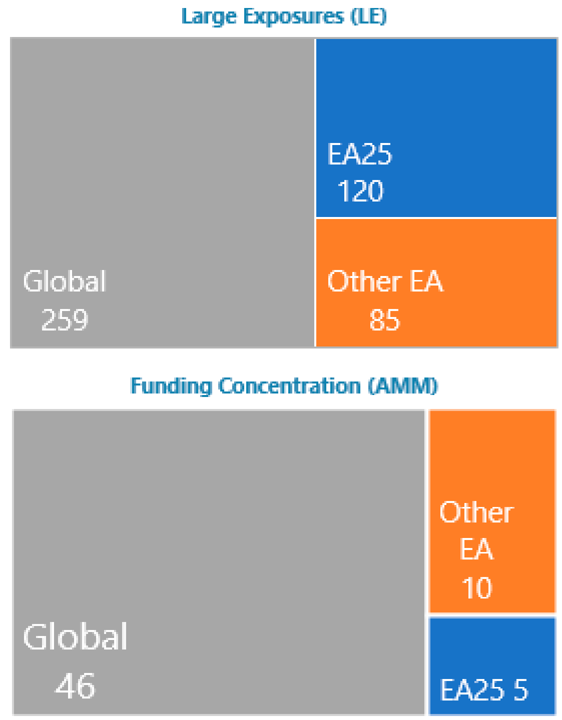
Appendix II Figure 1. Euro Area: Large Exposures Dataset

Exposure data matrix



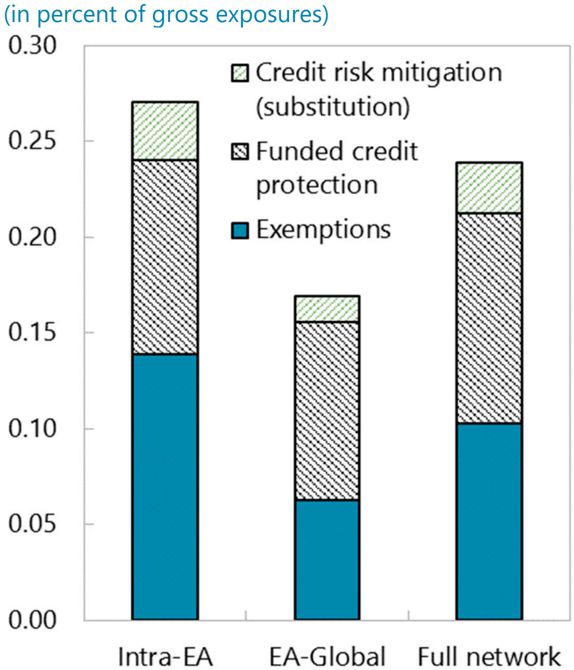
Scale of exposures data

(Billions of euros)

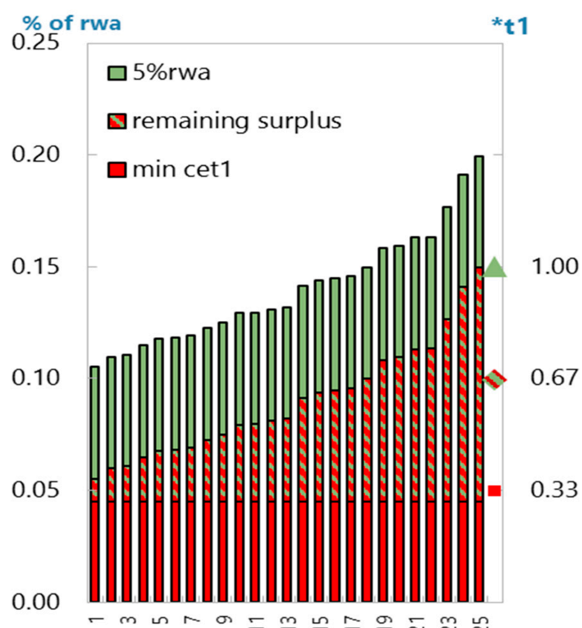


Exemptions and credit risk mitigation measures

(in percent of gross exposures)



Capital buffers



Sources: ECB, and IMF staff calculations.

MARKET-BASED INTERCONNECTEDNESS ANALYSIS[32]

A. Introduction

63. Banking system interconnectedness is central to financial stability. It features prominently in key aspects of systemic risk, that is, the system-wide connectedness. Indeed, interconnectedness, along with size and complexity, for example, is one of the main criteria used by the Financial Stability Board (FSB) when determining globally systemically important banks (G-SIBs).

64. In this chapter, market-based spillover measures are used to gauge the interconnectedness of the euro area banking system. Equity price data are used to estimate spillovers between euro area and non-euro area listed banks across 28 countries over 2006–2017. While bank-level data are used, the focus is on net spillovers (the difference between outward and inward spillovers) from the perspective of the euro area banking system vis-à-vis selected non-EA banking systems. This focus is partly motivated by the fact that the EA has one of the largest, most complex, and globally interconnected banking systems in the world; and is home to several G-SIBs.

65. Our proposed methodological framework is novel, in that it entails deriving conditional net spillover distributions. Specifically, quantile regressions are used to generate distributions of net spillovers conditional on banking system characteristics (for example, solvency, profitability, and asset quality metrics) and macroeconomic conditions (for instance, real GDP growth). This allows us to gauge how changes in such determinants influence the entire distribution of net spillovers. Put differently, going beyond the mean, the chapter quantifies how shifts in selected bank characteristics affect the variance, skewness, kurtosis, and hence more generally, the conditional distributions of net spillovers. The framework thus stands in contrast to more traditional linear empirical strategies which, conditional on determinants, seek to analyze net spillovers solely in terms of the mean outcome.[33]

66. While the a priori link between bank-specific characteristics and average spillovers maybe relatively intuitive, the degree to which such characteristics influence the conditional distribution of net spillovers is less clear, warranting an empirical investigation. For example, a natural conjecture would be that greater capitalization would reduce inwards spillovers on average. However, the implications for higher moments, and the distribution of (net) spillovers is less clear. Likewise, some determinants may primarily shift the conditional distribution's central tendency

[32] This chapter was prepared by Selim Elekdag, Sheheryar Malik, and Tadeusz Galeza, all Monetary and Capital Markets Department, IMF.

[33] The bulk of earlier work measures financial system interconnectedness without exploring the drivers of these dynamics. For example, Diebold and Yilmaz (2009) propose a simple quantitative measure of interdependence called a spillover index. They build on a vast literature including, for example, Engle (1990) and Engle and Kelly (2012). Demirer and others (2017) focus on global banks, and illustrate connectedness via network maps and summarize dynamics using rolling windows. However, except for IMF (2016) and Malik and Xu (2017), the literature stops short of explaining the potential factors influencing these patterns. Moreover, all papers focus on average spillover dynamics and do not consider higher moments or distributions.

(including the average), while others may tend to operate more on the tails, that is, largely impacting tail risks. Classifying determinants based on how they impact different segments of the distribution could be informative from a risk management perspective. Importantly, the proposed framework allows formal quantification of the likelihood of a banking system being a recipient or transmitter of spillovers, and how this likelihood would vary as changes in various determinants (such as capital buffers, profitability, and asset quality metrics) shift the conditional distribution of net spillovers.

67. The main findings can be summarized as follows:

- The EA banking system is equally as likely to be a recipient of inward spillovers from the U.S. and other European banking systems as it is to be a transmitter of outward spillovers to these systems. However, given its more leptokurtic shape of the distribution, EA net spillovers vis-à-vis extra-EA banking systems are more prone to tail risks. The EA appears much more likely to be a transmitter of outward spillovers to banking systems in emerging and (other) advanced economies, than being a recipient

- Stronger bank fundamentals reduce the likelihood of inward spillovers from the rest of the world not only on average, but also in terms of tail risks. In particular, lower NPL ratios, greater profitability, and higher capitalization levels are shown to decrease the probability of inward spillovers to the euro area banking system from the rest of the world.

- Evidence over the past five years suggests stronger bank fundamentals (such as better asset quality), may reduce inwards spillovers to a greater degree relative to earlier in the decade.

- Evidence is found that progressively stronger fundamentals can enhance the euro area banking system's resilience to inward spillovers without necessarily aggravating outward spillovers. Thus, strong euro area fundamentals appear to enhance the stability of other regions.

B. General Framework: An Overview

This section begins with a summary of the market-based spillovers measure used, and then moves on to the novel contribution of the chapter which is the derivation of probability distribution of net spillovers conditional on selected determinants.

Measuring Spillovers

68. Within the broader context of market-based interconnectedness, spillovers could be considered a directional concept. At any point in time, a financial entity can simultaneously act as a potential transmitter of shocks to market prices (outward spillovers) and receiver of shocks (inward spillovers), vis-à-vis other entities in an interconnected system. A "net" measure of spillovers for a particular entity, conceptualized as the difference in magnitudes between outward and inward spillovers, serves to capture the balance of risks associated with these market-based interconnectedness metrics. Given such a construct, negative net spillovers imply that the entity under consideration is a net receiver of spillovers, whereas a positive measure would correspond to the entity acting as a net transmitter.[34]

69. From a practical standpoint, one particular way to obtain market-based spillovers measures is via the Diebold-Yilmaz (2014, 2015) approach (DY, henceforth). This approach relies on estimating a vector autoregressive (VAR) model, employing time series data for a set of banks (in this case, on daily equity returns). Within the VAR framework, spillover metrics are derived via a forecast error variance decomposition, which quantifies the proportion of return variability (contemporaneous and H-steps ahead) of a particular bank *i,* that can be attributed to shocks to returns of another bank *j*, for instance.[35] This quantity, $C^H_{i\leftarrow j}$ say, is taken to proxy the spillover from *j* to *i*. Conversely, the proportion of *j*'s return variability, given shocks to bank *i*'s returns can also be computed. This would correspond to spillover from i towards *j*, i.e., $C^H_{i\rightarrow j}$. It follows that a net spillover measure for bank i vis-à-vis *j* would simply be the difference:

$$netspillover_{i\leftrightarrow j} = C^H_{i\rightarrow j} - C^H_{i\leftarrow j}. \quad (1)$$

Generating Conditional Distributions

70. Assuming availability of net spillover measure, the link with determinants can be made using quantile regressions (Koenker and Bassett, 1978 and Koenker, 2005). For net spillover series corresponding to a single bank i vis-à-vis another bank *j* the equation to be estimated could be written follows:

$$\left(netspillover^q_{i\leftrightarrow j,t} =\right) y^q_{(i),t} = \alpha + \beta^q Bank_{(i),t} + \gamma^q Macro_{(i),t} + \epsilon^q_t \quad (2)$$

where the time subscript t (=1,…,*T*), denotes quarters; $Bank$ denotes a $B\times T$ vector of bank *i*'s balance sheet characteristics; $Macro$ denotes an $M\times T$ vector of macroeconomic conditions corresponding to the country where bank i is headquartered; and q denotes various percentiles of interest for which equation (2) is to be estimated, that is, q = {0.05; 0.25; 0.50; 0.75; 0.95}. The estimated conditional quantile function (inverse cumulative distribution function) would in turn correspond to: $\hat{y}^q_{(i),t}(= \alpha + \hat{\beta}^q Bank_{(i),t} + \hat{\gamma}^q Macro_{(i),t})$.

71. Given the noisiness of quantile functions estimates in practice, recovering the corresponding PDF will require smoothing of the quantile function. In this chapter, in line with

[34] The focus on net spillovers is to help facilitate the analysis and to present a summary metric, and not necessarily because net spillovers are more relevant to systemic risk analysis than gross spillovers.

[35] Following Demirer and others (2017), the elastic net estimator (Zou and Hastie, 2005) is used to estimate the high-dimensional VAR. This blends shrinkage and selection to recover degrees of freedom, to deal with the "curse of dimensionality." Essentially, the elastic net estimator blends the Lasso (Tibshirani, 1996) and ridge regression. For the error variance decomposition, the Generalized Variance Decomposition (GVD) (Koop, Pesaran and Potter, 1996 and Pesaran and Shin, 1998) is applied. Compared to the Cholesky decomposition proposed by Sims (1980) and related identification strategies, GVD is invariant to the ordering of variables, which offers more flexibility in modeling strategy without making any a priori assumption on the sequence of responses.

the approach of Adrian, Boyarchenko, and Giannone (2017), (see also GFSR 2017), this is accomplished via fitting a (parametric form) 'skewed' t-distribution:

$$f(y;\mu,s,v,\xi)=\begin{cases}\dfrac{2}{\xi+\dfrac{1}{\xi}}\xi\, g(z), & z<0\\ \dfrac{2}{\xi+\dfrac{1}{\xi}}\, g(z)/\xi, & z\geq 0\end{cases}\qquad(3)$$

where $g(z)=\frac{1}{s}\bar{g}(z;\ v)$, with $\bar{g}(.)$ denoting the PDF of standard Student-t with v degrees of freedom; z is given by $\frac{y-\mu}{s}$, with μ and s referring to location and scale parameters, respectively. Skewness is governed by shape parameter ξ. This functional form for the skewed t-distribution is based on that motivated by Fernandez and Steel (1998), further explored and refined in Giot and Laurent (2003) and Lambert and Laurent (2002); see also Boudt, Peterson and Croux (2009).[36] For specified values for the conditioning variables (or point in time), four parameters $\{\mu,s,v,\xi\}$ of the implied density determined by minimizing the squared distance between the estimated quantile function, $\hat{y}^q$, and theoretical quantile function $y^{q,f}(\mu,s,v,\xi)$ corresponding to the above skewed-t distribution (see Giot and Laurent, 2003). Specifically, the 5th, 25th, 50th, 75th, and 95th percentiles can be matched via distance minimization:

$$\{\mu,s,v,\xi\}=\underset{\mu,s,v,\xi}{\mathbf{arg}\min}\sum_q\{\hat{y}^q-\ y^{q,f}(\mu,s,v,\xi)\}^2\quad(4)$$

where $\mu\in\mathbb{R}$, $s>0$, $v\geq 2$ and $\xi>0$. Notwithstanding the skewness property, the choice of a skewed-t functional form is advantageous from the perspective of flexibility. For example, as $v\to\infty$, $f(y;\mu,s,v,\xi)$ is characterized by tail properties resembling a Gaussian; moreover, the density is symmetric for $\xi=1$.

C. Data and Stylized Facts

This section reviews the publicly-available data used to estimate spillovers and some stylized facts, briefly presents an example illustrating how net spillovers have evolved over time, and then discusses the possible determinants of net spillovers.

Market-based Data

72. Market-based spillovers are derived using daily returns from equity price data for a sample of 93 global banks (Appendix II, Table 1). These banks are allocated to five regional

[36] Alternative specifications for the skewed *t*-distribution are present in literature, e.g., as put forth inter alia by Hansen (1994) and Azzalini and Capitanio (2003). These are essentially equivalent given a (nonlinear) transformation of the skewness parameter.

banking systems: euro area (EA), Other Europe (OE), the United States (U.S.), Advanced Economies, excluding U.S. and Europe (AE), and emerging markets (EM). In particular, OE includes banks headquartered in Sweden and the United Kingdom, whereas AE includes Australian, Canadian, and Japanese banks (Appendix II, Table 1). The sample is restricted only to banks which have been publicly-traded since around 2005 with consistently available equity price data for each bank over the period January 1, 2006 to June 1, 2017. Our coverage of EA banks constitutes around 50 percent of that banking system's assets.[37] All non-EA banks (allocated across the remaining regions) are drawn from a list of the top 100 (publicly-traded) global banks by assets size and is in line with Demirer and others (2017). Descriptive statistics indicate that average equity returns for all banks over the sample was slightly negative, likely reflecting the legacy of the global financial crisis (Appendix I, Table 1). In addition to applying the DY methodology to daily log returns, intra-day equity volatility series are also considered.[38] For each bank, this is computed as a function of the difference between maximum and minimum equity price, observed over a day; see Parkinson (1980).[39]

73. Given the primary interest is investigating spillovers across regional banking systems, the general framework discussed above will need to be modified. Specifically, to facilitate estimation with data pooled across constituent banks within these systems. Appendix III details these modifications, and also discusses reasons to opt for such an estimation strategy given constraints posed by the nature of empirical investigation, and data availability.

Evolution of Net Spillovers

74. To give a sense of how spillovers have changed over time, the example of net spillovers between the euro area and U.S. banking systems is considered. Overall, the dynamics of net spillovers indicate that the euro area banking system shifts between periods of being a net recipient of spillovers and a transmitter vis-à-vis the U.S. banking system. Key events have influenced the net spillovers between these two banking systems including standard and unconventional monetary policy actions as well as episodes of acute financial distress.[40]

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[37] It is important to note that market data is not available even for large euro area some banks (and therefore the sample here differs from that used in the balance sheet-based interconnected analysis, for instance). More generally, there are some caveats to using market-based data that need to be recognized. For example, (thinly-traded) markets can underreact in tranquil times and overreact during episodes of stress (possibly reflecting, for instance, herding behavior), and therefore may not fully capture the build-up and unwinding of certain vulnerabilities. Bank returns may also be impacted by board market developments unrelated to the performance of the bank under consideration. Note also that there is most likely a loss of information when transforming the higher-frequency market data to lower frequencies (via averaging) which is required as the balanced sheet data is only available on a quarterly basis.

[38] Accounting for various global factors as (exogenous) controls, such as measures of global interest rates as well as stock and bond market volatility metrics (VIX and the MOVE) does not materially change the spillover estimates.

[39] To control for the differences in trading hours due to time zones, average two-day log returns for equity prices in local currency are computed (see, for example, Forbes and Rigobon, 2002, and GFSR, April 2016b). In order to deal with holidays and missing observations, a day is removed if more than half of the entities have missing data; remaining missing observations are then interpolated.

[40] A 250-day window was used to calculate the spillovers, and a length of 150 days yields comparable results.

Figure 12. Net Spillovers 1/

(Index)

Sources: Bloomberg, and IMF staff calculations.

1/ Net spillovers between the euro area and U.S. banking systems are shown as an example. To help shed light on the dynamics, a selected list of key events includes the following: January 22, 2008: Fed cuts base rate; September 15, 2008: Lehman's collapse; November 25, 2008: QE1 announced; May 6, 2010: Concerns that euro area distress is spreading effectively caused a severe market sell off, particularly in the United States where electronic trading glitches combined with a high volume sell off produced a nearly 1,000 point intra-day drop in the Dow Jones Industrial Average; May 2, 2010: First economic adjustment program for Greece; November 3, 2010: QE2 announced; January, 2011: Fitch downgrades Greek debt to below investment grade status; July 21, 2011: EU reaches agreement on how to deal with the Greek debt crisis; August 18, 2011: European stock markets suffer losses given persistent concerns about world economic outlook; September 21, 2011: Operation Twist announced; October 10, 2011: Dexia nationalized; September 13, 2012: QE3 announced; May 8, 2013: ECB cuts rate; December 15, 2015: Fed raises policy rate.

Determinants of Net Spillovers

75. In this sub-section, the estimated (net) spillover measures are linked to their potential determinants. The primarily focus is on bank-specific financial soundness indicators as possible determinants which include capital buffers, profitability, asset quality, and a measure of short-term liquidity. Country-specific information on GDP developments is also conditioned upon. Table 12 summarizes how these determinants are proxied. Since balance sheet information tends to be recorded only at a quarterly or annual frequency, the selection of variables selected to proxy the aforementioned bank-level characteristics was guided by the consistent availability of quarterly data, covering the entire sample (2006 Q1–2017 Q2). To align data frequencies, the estimated daily (net) spillover series were converted to quarterly averages.

76. Descriptive statistics reveal some insightful findings regarding the bank-specific determinants. Profitability and asset quality, measured with ROA and the NPL ratio, are of particular interest. While average ROA is 0.15 percent, the median is 0.31 percent suggesting a profitability distribution with a long left tail populated by weaker banks (Appendix I, Table 2). Likewise, the average NPL ratio exceeds the median suggesting that asset quality issues are plaguing some banks to a much greater extent.

Table 12. Determinants

Characteristics	Proxy variable	Label
Banks specific		
Capital buffers	Ratio of Tier 1 capital to total assets	'Tier 1'
Profitability	Return on assets	'ROA'
Asset Quality	Ratio of nonperforming loans to total loans	'NPL'
Short term liquidity	Ratio of cash and marketable securities to total liabilities	'St. Liq.'
Country specific		
GDP growth	Quarter-on-quarter growth rate	'GDP'

Sources: Bloomberg, Datastream, Bankscope, SNL, and IMF staff.

Notes: ROA is computed as ratio of trailing 12-month net income to average total assets. Country-specific information pertains to the country where bank is headquartered.

D. Pooled OLS Versus Quantile Regressions

Before proceeding to quantile regression analysis, this section discusses the results based on more familiar OLS regressions to get a broad sense of the link between net spillovers and their potential determinants. The expectation is that better financial soundness indicators would reduce the susceptibility to inward spillovers.

Pooled OLS Regression

77. There is an intuitive and statistically significant relationship between net spillovers and bank-specific characteristics. As a first pass, and to present some further stylized facts, OLS regressions are used to uncover the drivers of the net spillover measures.[41] It is evident from results presented in Table 13 that most of the included banking system characteristics have a significant impact on net spillovers (both based on equity returns and volatility). The results are intuitive in that better capitalization, and for example, liquidity metrics are associated with higher net spillovers (which likely reflect, lower inward spillovers). Likewise, in line with expectations, the coefficient on the NPL ratio is negative and is statistically significant across the board. Real GDP growth appears to be statistically significant only the case of U.S. return and AE volatility spillovers.

[41] Although these OLS regressions are not the main focus of the chapter, the results were robust when other variable combinations were considered, for instance, log(asset) to control for size or the growth rates of the other bank-specific characteristics (e.g., tier 1 capital ratios).

Table 13. Pooled OLS Regression Analysis

	Returns				Volatility			
***Net spillovers* EA:**	**OE**	**US**	**AE**	**EM**	**OE**	**US**	**AE**	**EM**
Tier 1 Capital Ratio	0.43**	0.11**	0.18**	0.12**	0.57**	0.30**	0.06**	0.08**
	(0.64)	(0.03)	(0.03)	(0.03)	(0.06)	(0.04)	(0.03)	(0.02)
Return on Assets	0.29**	0.07	0.17**	0.21**	0.02	0.08	0.01	0.05
(ROA)	(0.11)	(0.06)	(0.07)	(0.06)	(0.12)	(0.08)	(0.06)	(0.04)
NPL ratio	-0.15**	-0.09**	-0.14**	-0.12**	-0.14**	-0.05**	-0.09**	-0.07**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)
Short-term	0.15**	0.07**	0.08**	0.07**	0.18**	0.11**	0.05**	0.06**
Liquidity	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
GDP growth	0.02	0.03**	0.01	0.01	0.02	0.01	0.03**	-0.01
(country-specific)	(0.03)	(0.01)	(0.49)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	-5.07**	-1.76**	2.46**	2.64**	-6.12**	-4.92**	1.55**	1.48**
	(0.62)	(0.38)	(0.37)	(0.32)	(0.69)	(0.44)	(0.32)	(0.26)
Observations	1424	1424	1424	1424	1424	1424	1424	1424
R^2	0.32	0.29	0.26	0.22	0.30	0.24	0.25	0.23

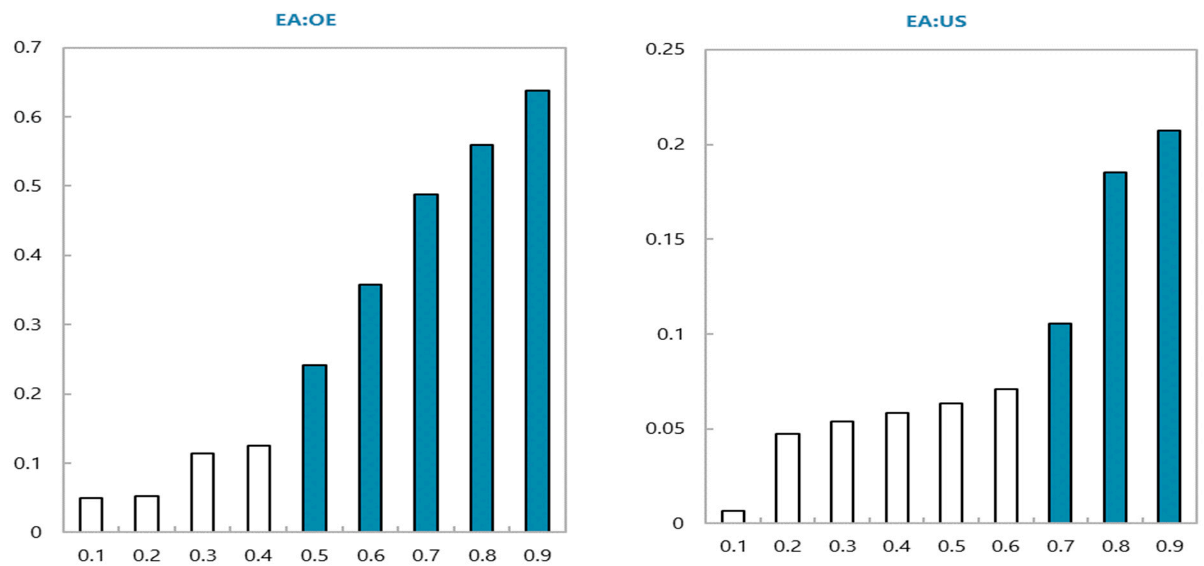
Note: The dependent variable, *net spillover* EA, refers to the dependent variable, net spillovers. (**) denotes significance at 5 percent level. Panel corrected standard errors computed using cross-sectional weights reported in parentheses.

Quantile Regression Analysis

78. Quantile regressions capture non-linear relationships between net spillovers and bank-specific characteristics. Recall that the OLS analysis indicated that the link between profitability (ROA) and net spillovers was not as strong relative to other bank-specific determinants, especially in the case of volatility spillovers. However, this result may be masking insightful non-linearities across different quantiles.

79. To this end, the OLS regressions discussed above are re-estimated, but using quantile regression analysis over a range of deciles. In this case, there would be 9 coefficients linking ROA to net spillovers (one coefficient for each decile), which are shown in Figure 13. This example includes net spillovers between the EA and two other region banking systems: Other Europe (OE) and the U.S. In both cases, the coefficients increase progressively from the lower to the upper deciles. At the same time, shaded bars denote statistically significant coefficients (at the 5 percent level), thereby highlighting the non-linear relationship between profitability and net spillovers—which is especially striking in the case of EA:U.S. spillovers. In sum, while a meaningful impact of profitability on the central tendency of net spillovers is evident in the case of EA:OE spillovers, this impact is much larger towards the right tail of the conditional distributions of net EA:OE and EA:US spillovers.

Figure 13. Non-Linear Impact of Profitability on Spillovers Across Percentiles



Note: Bars denote magnitudes of quantile coefficients. Shaded bars indicate statistical significance at the 5 percent level.

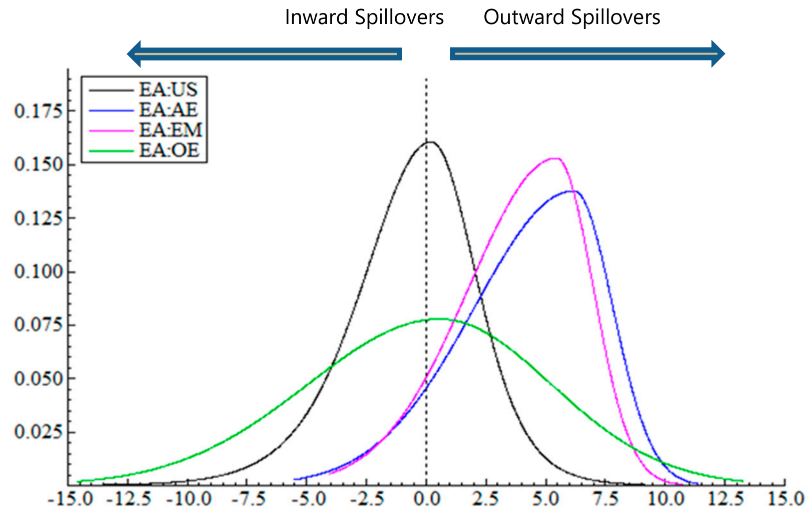
E. Conditional Spillover Distributions

This section sets the stage by discussing the baseline conditional distributions of net spillovers. Then various illustrative scenarios are considered whereby shifts in selected bank-specific determinants alter the shape of the net spillover distributions.

Baseline Distributions

80. The baseline conditional distributions of euro area net spillovers differ across regions. Figure 14 displays the baseline conditional probability density function of net spillovers, which is estimated by setting the values of all determinants to their sample averages. Four distributions are shown, corresponding to the euro area's net spillovers vis-à-vis banking systems in Other Europe (OE), the United States (U.S.), Advanced Economies, excluding U.S. and those in Europe (AE), and emerging markets (EM). In terms of interpretation, moving rightwards (leftwards) along the horizontal axis corresponds to increasing magnitudes of outward (inward) spillovers. Given the similar probability mass on either side of zero, visual inspection of these densities suggests that the EA banking system is equally as likely to be a recipient of an inward spillovers from OE and U.S. banking systems, as it is to be a transmitter of outward spillovers to these systems. However, given its more leptokurtic shape, EA net spillovers vis-à-vis OE are more prone to tail risks. The EA appears much more likely to be a transmitter of outward spillovers to AE and EM banking systems, than being a recipient.

Figure 14. Baseline Probability Density Functions



Source: IMF staff estimates.

Note: x-axis denotes index values. Densities are assumed to have a skewed-t form.

81. **The conditional distributions facilitate quantitative assessments.** The probability of EA net spillovers being less than or equal to zero is computed by integrating the area under the each of the baseline densities. These resulting cumulative probabilities, *prob*(*net spillover* EA: non-EA ≤ 0), are presented in Table 14, and are a convenient way of summarizing net spillovers across regions. The initial assessment regarding the likelihood of inward spillovers from each of the non-EA systems (Figure 14) broadly accords with this formal quantification (Table 14).

Table 14. Probability of Inward Spillover—Baseline
(Percent)

prob(*netspill*EA:US ≤0)	*prob*(*netspill*EA:AE ≤0)	*prob*(*netspill* EA:EM ≤0)	*prob*(*netspill* EA:OE ≤0)
56.1	10.1	9.7	49.7

Source: IMF staff estimates.

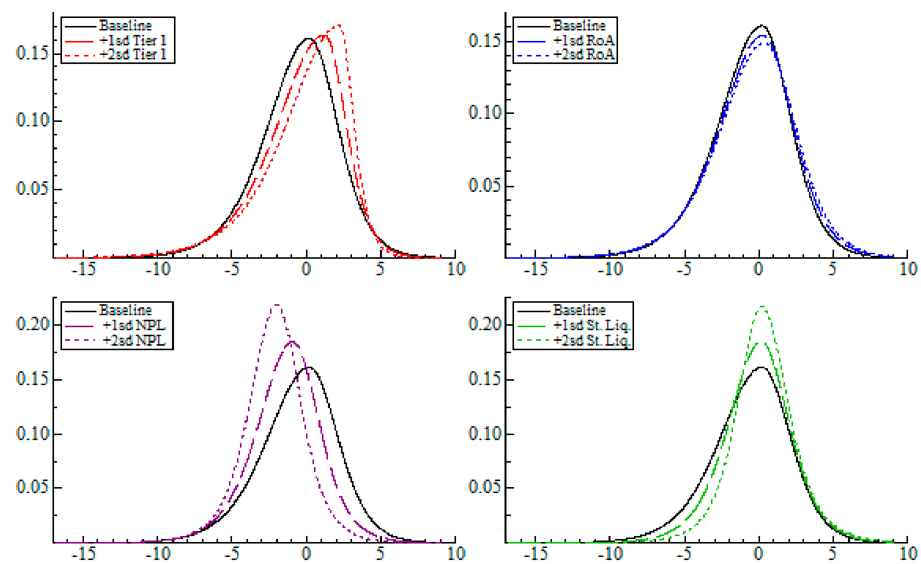
Note: '*netspill*' abbreviates net spillovers. *prob*(*netspill*EA: non-EA ≤ 0) computations are based on the cumulative distribution functions corresponding to a skewed-t form.

Scenario Analysis

82. **The impact of changes to the bank-specific determinants on the baseline spillover densities is now examined.** Both one and two standard deviation shocks relative to their average (baseline) values are used when generating the new (shocked) distributions. Note that for a particular determinant being shocked, a density's central tendency may shift with minimal effect on tails or vice versa. In other instances there could be simultaneous shifts in the central tendency and tails of the distributions.

83. In general, the results suggest that stronger bank fundamentals reduce net spillovers from the rest of the world not only on average, but also in terms of tail risks. Densities conditional on shocked determinants are compared with their baselines in Figures 15–18. Consider the example of net spillovers between the EA and U.S. banking systems (Figure 15). Relative to the baseline, an increase in capital buffers appears to shift primarily the mode of the density, with both tails remaining anchored. As a result, these changes in the moments of the density translate into a decline in the probability of inward spillover to the EA banking system (Table 15). However, an increase in NPL ratio results in leftward shift in the central tendency accompanied with a retrenching of the right-tail thereby raising the likelihood of inward spillovers. In fact, on average, variations in the NPL ratio result in the largest changes in the probability of inward EA spillovers from the other banking systems. While the figures focus on rising NPL ratios, Table 16 considers negative shocks, which summarize the spillover implications owing to a lower NPL ratio (and complements Table 15).

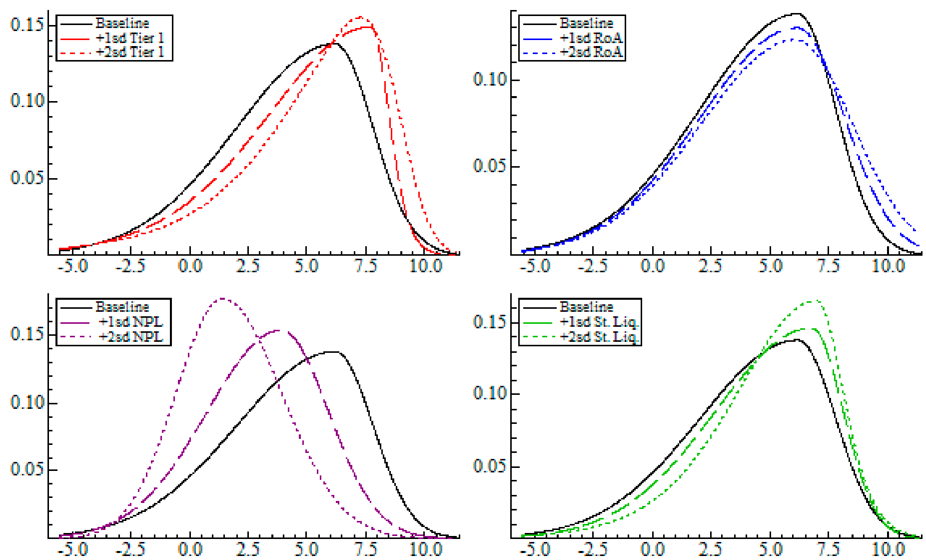
Figure 15. Shocks to Baseline Probability Density Functions, EA:US



Source: IMF staff estimates.

Note: Densities are assumed to have a skewed-*t* form.

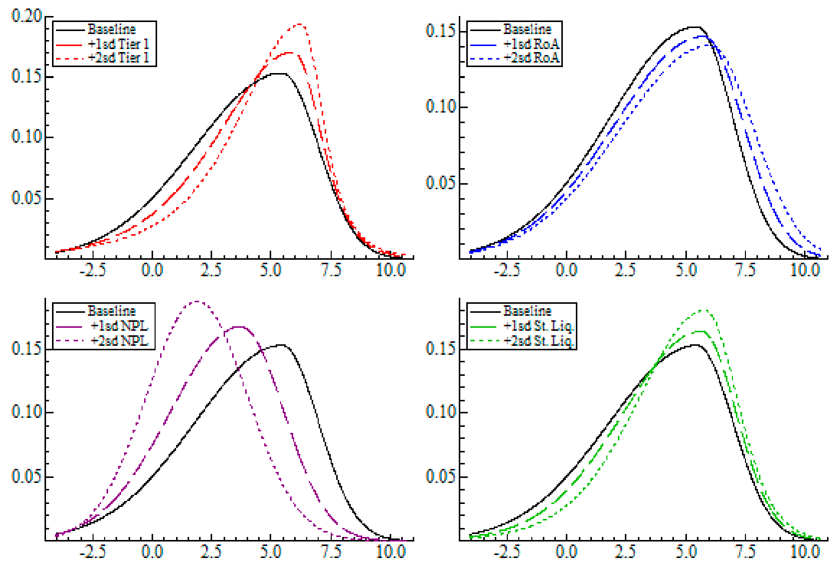
Figure 16. Shocks to Baseline Probability Density Functions, EA:AE



Source: IMF staff estimates.

Note: Densities are assumed to have a skewed-*t* form.

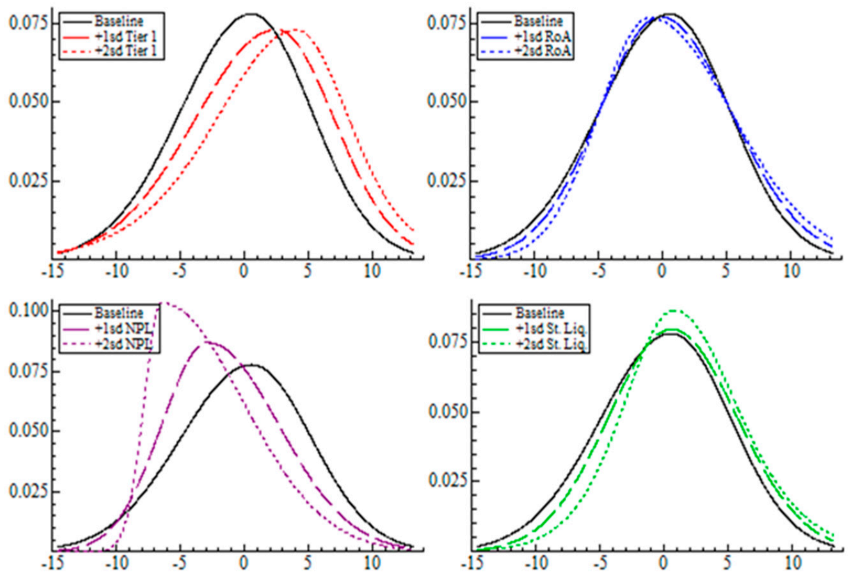
Figure 17. Shocks to Baseline Probability Density Functions, EA:EM



Source: IMF staff estimates.

Note: Densities are assumed to have a skewed-*t* form.

Figure 18. Shocks to Baseline Probability Density Functions, EA:OE



Source: IMF staff estimates.

Note: Densities are assumed to have a skewed-*t* form.

Table 15. Probability of Inward Spillover—Positive Shocks to Baseline

(In percent)

	prob(*netspill* EA:US ≤0)		*prob*(*netspill* EA:AE ≤0)		*prob*(*netspill* EA:EM ≤0)		*prob* (*netspill* EA:OE ≤0)	
Baseline	56.1		10.1		9.7		49.7	
Shock	+1 sd	+2 sd	+1 sd	+2 sd	+1 sd	+2 sd	+1 sd	+2 sd
Tier 1	49.1	43	8.8	7.6	8.7	8.3	40.5	32.6
ROA	54.1	52.2	9.1	8.3	8.6	7.7	47.7	46.1
NPL	72.1	87.6	13.2	21.1	12.7	18.8	63.2	74.4
St. Liq.	51	44.1	7.6	5.7	6.9	4.8	44.3	37.9

Source: IMF staff estimates.

Note: '*netspill*' abbreviates net spillovers. *prob*(*netspillover* EA: non-EA ≤ 0) computations are based on the cumulative distribution functions corresponding to a skewed-*t* form. 'sd' refers to standard deviations.

Table 16. Probability of Inward Spillover—Negative Shocks to Baseline
(Percent)

	p(*netspill* EA:US ≤0)		*p*(*netspill* EA:AE ≤0)		*p*(*netspill* EA:EM ≤0)		*p*(*netspill* EA:OE ≤0)	
Baseline	56.1		10.1		9.7		49.7	
Shock	-1 sd	- 2 sd	-1 sd	-2 sd	-1 sd	-2 sd	-1 sd	-2 sd
Tier 1	63.2	69.5	11.2	13.2	10.4	11.4	60.8	71.8
ROA	58.1	60.4	10.7	10.8	10.5	11.1	52	54.7
NPL	43.5	34.6	7.9	6.8	7.4	6.7	39.1	32.2
St. Liq.	56	63.2	12.7	15.8	13	16.4	54.8	59.6

Source: IMF staff estimates.

Note: '*netspill*' abbreviates net spillovers. *p*(*netspillover* EA: non-EA ≤ 0) computations are based on the cumulative distribution functions corresponding to a skewed-*t* form. 'sd' refers to standard deviations.

84. The reduction of the probability of inward spillovers differs across regions and the bank-specific shocks under consideration. For instance, higher profitability leads to a similar decline in the probability of inward EA spillovers vis-à-vis the U.S. and OE banking systems (Tables 15–16). However, relative to profitability, greater capitalization results in even greater decreases, especially in the context of EA:OE spillovers. This said, a decline in the NPL ratio results in the greatest decline in the probability of inward spillovers for all banking systems.

85. Shocks can also affect the spillover distributions in an asymmetric manner given the shape of the baseline and shocked distributions. Such differences are greatest in the case of NPLs (when comparing baseline and shocked probabilities): although a two standard deviation increase in the ratio increases the probability of inward spillovers by about 32 percentage points (Table 15), the analogous decrease results in a decline of about 21 percentage points (Table 16). This result underscores how much a deterioration in key bank fundamentals can heightened vulnerabilities to spillovers from other banking systems.

Pre- and Post-Sample Analysis

86. The relationship between spillovers and bank fundamentals has evolved over the past decade. The models are re-estimated using two sub-samples: (1) 2006 Q1–2012 Q3, and (2) 2012 Q4–2017 Q2. The results are shown in Figure 19, and documented in Table 17. Stronger bank-specific fundamentals, such as better asset quality, in recent years appear to reduce the probability of inwards spillovers to a greater extent relative to earlier periods.

Table 17. Probability of Inward Spillover—Comparing Pre-, and Post-Sample

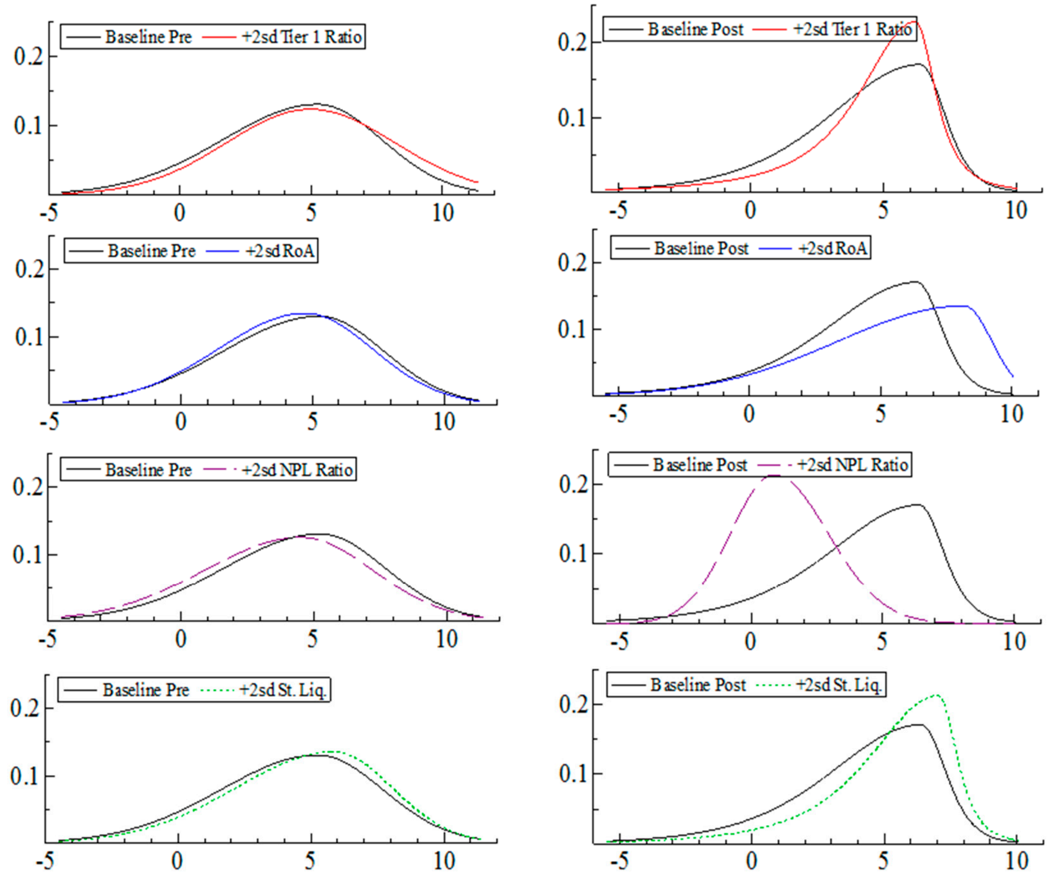
(Percent)

	p(*netspill* EA:US ≤0)		*p*(*netspill* EA:AE ≤0)		*p*(*netspill* EA:EM ≤0)		*p*(*netspill* EA:OE ≤0)	
Sample split	*Pre*	*Post*	*Pre*	*Post*	*Pre*	*Post*	*Pre*	*Post*
Baseline	54.0	55.0	9.0	9.1	8.1	10.0	56.1	43.2
Shock	+2 sd	+2 sd	+2sd	+2 sd	+2 sd	+2 sd	+2 sd	+2 sd
Tier 1 Ratio	43.2	53.1	6.4	8.0	4.1	9.1	50.0	38.1
ROA	51.3	47.2	8.1	8.1	7.0	7.0	54.1	31.1
NPL	58.4	83.1	12.3	26.2	11.2	28.0	66.2	76.4
St. Liq.	48.0	42.1	7.1	6.0	7.0	5.0	50.3	22.7

Source: IMF staff estimates.

Note: '*netspill*' abbreviates net spillovers. *p*(*netspill* EA: non-EA ≤ 0) computations are based on the cumulative distribution functions corresponding to a skewed-*t* form. 'sd' refers to standard deviations.

Figure 19. Shocks to Baseline Probability Density Functions, EA:AE Pre-, and Post- Sample Comparison



Source: IMF staff estimates.

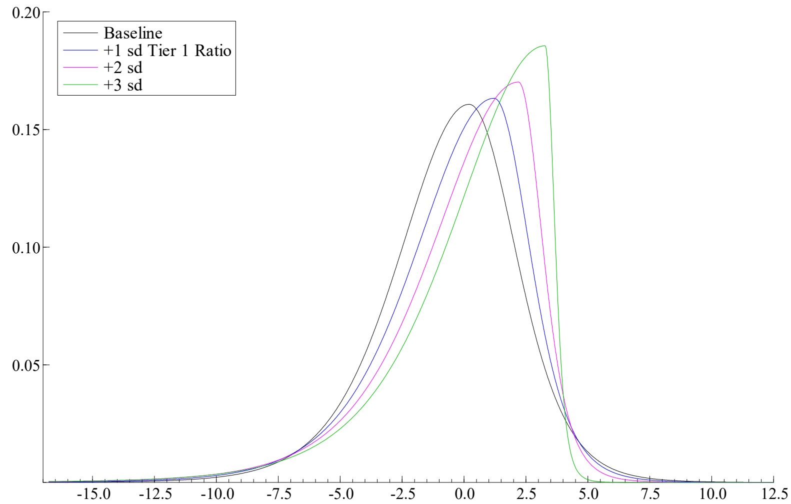
Note: Densities are assumed to have a skewed-*t* form.

Improved Fundamentals and Positive Externalities

87. The impact of progressively stronger fundamentals on the probability of outward spillovers is now investigated. Figure 20 demonstrates the limiting behavior of conditional net spillover distributions due to progressively higher EA capitalization ratios. Bilateral spillovers between the euro area and U.S. bank systems is used as an illustration. Overall, the findings suggest that stronger fundamentals can improve a banking system's resilience to inward spillovers without necessarily aggravating outward spillovers. This is evident in the variance of the distributions progressively tightening around a particular point of the distributions' support (that is, the central tendency stops shifting rightwards). Given that an upper bound on magnitude of outward spillover exists (in the limit) strong euro area fundamentals appear to enhance the stability of other regions. Broadly similar results are found for other bank fundamentals (for instance, NPL ratios) and the other three regions.

Figure 20. Impact of Improved Fundamentals

EA:US



Source: IMF staff estimates.

Note: Densities are assumed to have a skewed-*t* form.

Spillovers Within the Euro Area

88. **Although not the focus of this chapter, the analysis also considered within euro area banking spillovers.** Recall that the euro area was taken as a single banking system in the discussions above. Now, each of the 10 euro area countries in the sample correspond to a banking system. While the results are suppressed for brevity, spillovers across these 10 countries was analyzed using the same approach outlined above. Overall, consistent with the results discussed above, enhanced banking soundness in a euro area country reduces the likelihood of inward spillovers from the rest of the euro area, both in terms of central tendencies, but also in terms of tail risks.

F. Conclusions and Policy Implications

89. **This chapter proposes a novel framework to quantify and appraise risks associated with euro area banking spillovers.** The framework derives probability distributions of net euro area spillovers conditional on selected determinants vis-à-vis other global banking systems. The findings suggest that stronger bank fundamentals (lower NPL ratios, greater profitability, and higher capitalization levels) reduce net spillovers to the euro area banking system from the rest of the world not only on average, but also in terms of tail risks. Moreover, such effects appear to have strengthen in recent years. Increasingly stronger fundamentals can enhance the euro area banking system's resilience to inward spillovers without necessarily aggravating outward spillovers.

90. **Even though EA banking system soundness indicators have been improving, addressing certain structural challenges could further reduce vulnerability to inward spillovers.** EA banks' capital ratios have risen on average, capital quality has improved, and funding

has become more stable as banks are increasingly relying on deposits. At the same time, despite improvements, progress in reducing NPLs remains uneven and bank profitability remains generally low. Therefore, some banks in particular, should take advantage of the current upswing to resolutely address their NPL stocks. In addition, greater cost efficiency (via digitization, for example) and a tailored approach to revamping business models could support the profitability prospects of many banks. Further progress on both fronts would reduce the likelihood of inwards spillovers to the EA banking system. Relatedly, the interconnectedness framework—already very sophisticated—could be further enhanced by developing tools that help quantify the tail risks associated with inward spillovers.

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Appendix I. Market and Balance Sheet Indicators

Appendix I Table 1. Market Based Indicators: Descriptive Statistics of Banks in the Sample 1/

(2006Q1–2017Q2, in percent)

	Equity returns 2/	Equity volatility 3/
Mean	-0.018	34.65
Median	0.000	25.67
Standard Deviation	2.81	33.53
Observations	280953	280953

Sources: Bloomberg, and IMF staff calculations.

1/ Sample includes top traded 93 banks by asset size
2/ Log returns based on the end of day equity price
3/ Intraday equity volatility, annualized.

Appendix I Table 2. Balance Sheet Determinants: Descriptive Statistics of Banks in the Sample 1/

(2006Q1–2017Q2, in percent)

	Tier 1 ratio 2/	Return on assets 3/	NPL ratio 4/	Liquidity 5/
Mean	10.80	0.15	7.74	9.79
Median	11.00	0.31	5.14	9.34
Standard Deviation	2.90	1.36	8.19	5.60
Observations	1242	1242	1242	1242

Sources: Bloomberg, and IMF staff calculations.

1/ Sample includes top traded 93 banks by asset size
2/ Ratio of Tier 1 capital to total assets
3/ Ratio of trailing 12-month income to average total assets
4/ Ratio of nonperforming loans to total loans
5/ Ratio of cash and marketable securities to total liabilities.

Appendix II Table 1. Sample of Banks and System Groupings

Euro Area	Other Europe	United States	Advanced Economies	Emerging Markets
Credit Agricole	Barclays	Bank of America	Mitsubishi UFJ Financial Group	Ping An Bank Co
BNP Paribas	Credit Suisse Group	Bank of New York Mellon	Sumitomo Mitsui Financial Group	Shanghai Pudong Development Bank Co
Deutsche Bank	HSBC Holdings	Citigroup	Mizuho Financial Group	Huaxia Bank Co
Societe Generale	Nordea Bank	Goldman Sachs Group	Industrial Bank of Korea	China Minsheng Banking Corp
ING	Royal Bank of Scotland Group	JPMorgan Chase & Co	Shinhan Financial Group	China Merchants Bank Co
Banco Santander	Standard Chartered	Morgan Stanley	Resona Holdings	Banco Bradesco
UniCredit	UBS Group	State Street Corp	Chiba Bank/The	Bank of Baroda
Allied Irish Banks	Danske Bank	Wells Fargo & Co	Shizuoka Bank/The	CIMB Group Holdings Bhd
Alpha Bank	DNB	American Express	Hokuhoku Financial Group	Turkiye Is Bankasi
Banco Bilbao Vizcaya Argentaria	Lloyds Banking Group	BB&T Corp	Nomura Holding	Itau Unibanco Holding
Banco Comercial Portugues	Skandinaviska Enskilda Banken	Capital One Financial Corp	Australia & New Zealand Banking Group	Malayan Banking Bhd
Bank of Ireland	Svenska Handelsbanken	Fifth Third Bancorp	Bank of Montreal	Sberbank of Russia PJSC
Bankinter	Swedbank	The PNC Financial Services Group Inc	The Bank of Nova Scotia	State Bank of India
BPER Banca		Regions Financial Corp	Commonwealth Bank of Australia	Standard Bank Group
Commerzbank		SunTrust Banks	Canadian Imperial Bank of Commerce	
Credit Industriel et Commercial		US Bancorp	DBS Group Holdings	
Dexia			Maquarie Group	
Erste Group Bank			National Bank of Canada	
National Bank of Greece			National Australia Bank	
Intesa Sanpaolo			Royal Bank of Canada	
KBC Group			The Toronto-Dominion Bank	
Natixis			United Overseas Bank	
Mediobanca			Westpac Bankingrp	
Banco de Sabadell				
Piraeus Bank				
Unione di Banche Italiane				
Unipol Gruppo Finanziaro				

Source: IMF Staff, Diebold-Yilmaz (2015).

Note: Advanced Economies excludes United States.

Appendix III. Pooled Estimation Strategy

The general framework discussed above needs to be modified given that the primary interest is investigating spillovers across regional banking systems. From the perspective of undertaking bank-by-bank estimation of equation (2) (as currently formulated), a time series dimension of T = 44 quarters would prove rather restrictive in terms of allowing accurate pinning down of parameters; especially in a quantile regression setting aimed at informing higher order moments. A case can be made to pooling time series information across individual banks by estimating a stacked version of equation (2), i.e., stacking the cross-section of N banks, say, providing and estimation sample of N×T. The advantage of pooling strategy is that whilst circumventing the practical issue of too few degrees of freedom, estimated parameters will correspond to an average across the cross section of banks, which aligns with the objective of analyzing results at the level of a system's average bank.

The definition of net spillovers needs to accordingly be adjusted. Given the specific focus of analyzing EA spillovers, information will be pooled over the cross-section of EA banks. To maintain consistency with regards to analyzing spillovers at the average EA/non-EA level within a pooled setting, expression (1) for net spillover will need to be modified. By way of example, suppose the non-EA system labeled AE consists of a set of banks indexed by *s*, where, *s* = 1,...,*S*. In this setting, $C^H_{i\to\bar{s}}$ $(=\frac{1}{S}\sum_s C^H_{i\to s})$ denotes spillover from EA bank *i*, to the average AE bank. Conversely, $C^H_{i\leftarrow\bar{s}}$ $(=\frac{1}{S}\sum_s C^H_{i\leftarrow s})$ corresponds to spillover to EA bank *i,* from the average AE bank. Therefore, the net spillover (for a single point in time) can be cast as:

$$netspillover_{i\leftrightarrow\bar{s}} = C^H_{i\to\bar{s}} - C^H_{i\leftarrow\bar{s}} \qquad (5)$$

Letting the number of EA banks in the total sample be given by N_{EA} such that *i* = 1, ..., N_{EA} with quarters *t,* such that *t* = 1,,...,*T*, the time series of net spillovers for each EA bank *i* vis-à-vis the average AE bank can then be stacked in order to estimate,

$$netspillover^q_{i\leftrightarrow\bar{s},t} = \boldsymbol{\alpha} + \mathbf{B}^{\mathrm{q}} Bank_{i,t} + \mathbf{G}^{\mathbf{q}} Macro_{i,t} + \epsilon^q_{i,t}. \quad (6)$$

Net spillovers of the EA system vis-s-vis the others is labeled as $netspillover$_EA: non-EA, where non-EA = {OE, AE, U.S., EM}.

CONTINGENT CLAIMS ANALYSIS[42]

91. This chapter presents an overview of the contingent claims analysis (CCA). An integrated contingent claims, mixed cross-section global vector autoregressive (CCA-MCS-GVAR) model is developed which combines a large scale empirical (MCS-GVAR) framework with CCA indicators and satellite modules.[43] The model was used to develop forecasts of bank and insurance companies' probability of defaults (PDs), conditional on the FSAP macrofinancial scenario assumptions.[44] In addition, these conditional forecasts are complemented with historical decompositions. A concise summary of the MCS-GVAR model structure is presented in Appendix I.

92. The framework encompasses banks, insurers, sovereigns, and the nonfinancial corporate sector. In particular, the CCA-MCS-GVAR combines PD estimates for financial institutions (30 in the model), insurers (11) and non-financial corporate (NFC) sectors (19), as well as sovereign credit spreads (for 19 sovereigns) in multi-country model, which includes supervisory ECB data on exposures of all banks and insurers relative to each other and to sovereigns and the nonfinancial sectors across countries. The need for market price data implies that the sample of banks is not the sample as in the case of the solvency and liquidity stress tests (see Appendix II for the list of banks, insurers, and sovereigns). The PD estimates are derived using CCA. The model is estimated based on data spanning the 1999Q1–2017Q4 period and used to produce scenario conditional forecasts for all model variables based on the FSAP macro-financial scenarios. The model contains the variables summarized in Table 18.

Table 18. Euro Area: Sectors and Model Variables

#	Cross-section	No. of institutions/countries	Model variables
1	Banks	30	PDs
2	Insurers	11	PDs
3	Sovereigns	19	CDS
4	Macro/corporate sectors	19	Real GDP
5			Nominal equity prices
6			NFC PDs

Source: Historical PDs are derived from Moody's CreditEdge database.

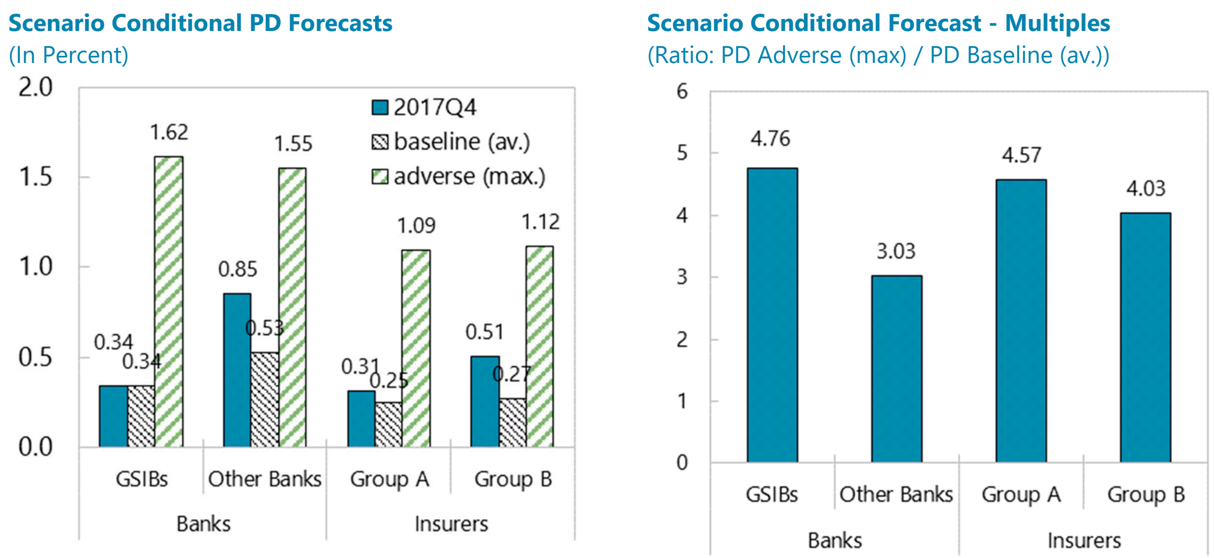
[42] This chapter was prepared by Dale Gray (Monetary and Capital Markets, IMF) and Marco Gross (ECB).

[43] The model structure employed for the analysis presented here combines some elements of different GVAR variants developed in the past. The inclusion of CCA-based indicators in a GVAR setting, as one element, has been pursued in Gray, Gross, Paredes, Sydow (2013), "Modeling banking, sovereign, and macro risk in a CCA Global VAR", IMF WP/13/218. The Mixed-Cross-Section feature of the GVAR, as a second core feature, has been developed in Gross and Kok (2013), "Measuring contagion potential among sovereigns and banks using a Mixed-Cross-Section GVAR", ECB WP No. 1570. It has been further extended to a semi-structural model set up and including more cross section types in Gross, Kok, Zochowski (2016), "The impact of bank capital on economic activity – Evidence from a Mixed-Cross-Section GVAR model", ECB WP No. 1888.

[44] Please see the EA FSAP Technical Note on Stress Testing the Banking Sector for details on the scenarios.

93. The scenario conditional forecasts for banks and insurers are shown in Figure 21. The groups A and B for insurers correspond to a group of "global" and "domestic" insurers, respectively (see Appendix II Table 2 for the list and group assignment). Figure 21 also shows the corresponding ratios of the PDs under the adverse and the baseline scenario.

Figure 21. Euro Area: Scenario Conditional PD Forecasts

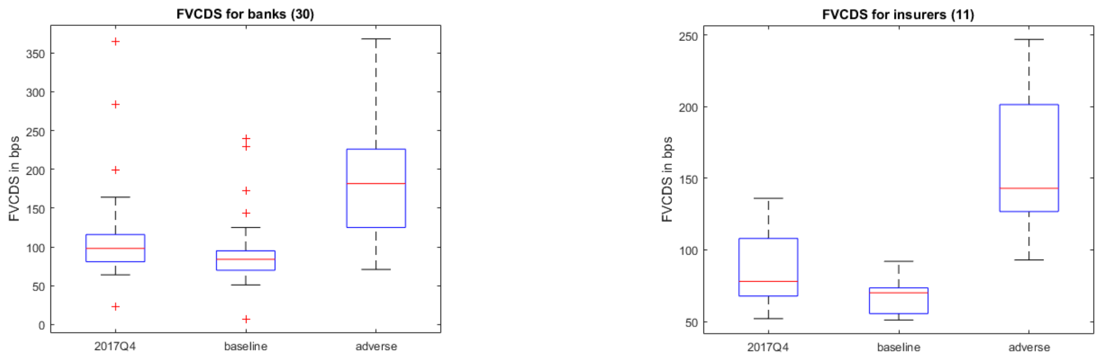


Source: IMF staff estimates.

94. Bank PDs are higher under the stress scenario relative to those of insurers. Under the adverse scenario, the G-SIB in the sample experience nearly a 5-fold increase of their baseline PDs compared to an approximate 3-fold increase of PDs for all other banks—which broadly corroborates the findings of the balance sheet-based solvency stress tests. One consistent result is that a minority of banks is much more vulnerable to an adverse shock than others. The increase in insurer PDs is from a low base

95. The adverse scenario would not only increase the average fair value CDS (FVCDS), but also lead to much greater dispersion (Figure 22). The box plots for the starting point (2017Q4) and the baseline (horizon average) and adverse scenario (horizon maximum) reflect the distribution of the underlying 30 banks' and 11 insurers' estimated level FVCDS. The mean increases by about 100 basis points for the banks, and for a substantial tail of banks the increase is much greater. A similar pattern is apparent among insurers. The FVCDS for some banks reach levels of about 350 basis points, that is, remain below 400 basis points which is deemed to be a critical value at which strong nonlinear effects in relation to the firms' wholesale funding costs have historically been observed to materialize (lenders to banks may be reluctant to roll over their debt, hence possibly implying liquidity shortages for banks). For insurers, the FVCDS stay a more comfortable margin below the 400-basis points threshold than do those of the banks.

Figure 22. Euro Area: Fair Value CDS Estimates for Banks and Insurers

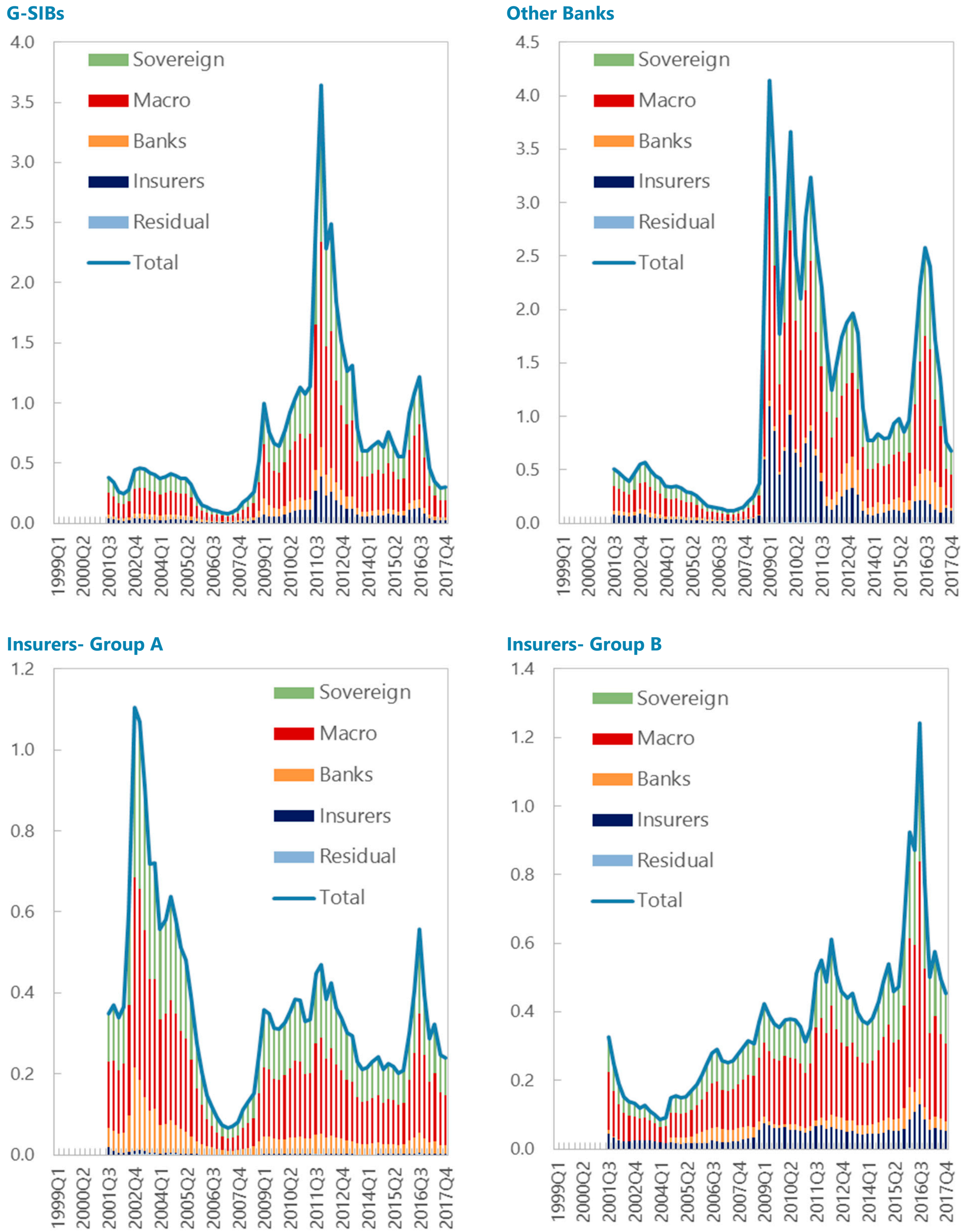


Source: IMF staff estimates.

Note: The box plots depict the distribution of fair value CDS (FVCDS) level spreads in the cross-sections of banks and insurers, respectively. The red lines indicate the median; the upper and lower edges of the boxes mark the 25th and 75th percentiles; the whiskers extend to the data points farthest out of the distributions that are not considered technical outliers yet. The red crosses mark "outliers" in a statistical sense as being farther away from the median.

96. The historical contributions of the model variables toward the PDs of banks and insurers are presented in Figure 23. Historical decompositions depict how the underlying contributions from other sectors explain PD dynamics banks and insurers. Some of the model variables' contributions are combined to not overload the charts with too much information: the sum of long-term rates and CDS contributions is referred to as the contribution of the "sovereign"; the sum of the contributions from nonfinancial corporate PDs, GDP growth and stock prices is referred to as the contribution of 'macro' in the charts. The figure illustrates how the sharp (bank and insurer) PD spikes are attributable to different variables over time.

Figure 23. Euro Area: Historical Contributions to the Dynamics of PDs of Banks and Insurers



Source: IMF staff estimates.

97. Table 19 summarizes the historical contribution estimates of different groups of model variables toward bank PDs, insurers' PDs and sovereign CDS. Four time windows are considered over which the average contributions were computed (consistent with the contributions visualized in Figure 23 for banks and insurers): a pre-crisis period from 1999Q1–2008Q3, an initial financial crisis period covering 2008Q4–2009Q4, the sovereign debt crisis from 2010Q1–2012Q4, and the remainder of the sample from 2013Q1–2017Q4.

Table 19. Euro Area: Historical Contributions to Changes in Variation of Bank, Insurer, and Sovereign PDs

(Percent)

			Banks - Grouping 2		Insurers		Sovereigns 1/
			G-SIB	no G-SIB	Group A	Group B	
Average PDs		Pre-crisis	0.3	0.3	0.3	0.5	14
		Fin. crisis	0.8	2.8	0.3	1.1	179
		Sov. debt crisis	1.9	2.3	0.4	0.6	494
		after	0.8	1.5	0.4	0.6	183
historical contri-butions	**Banks** (PDs)	Pre-crisis	9	7	11	8	14
		Fin. crisis	10	1	10	4	45
		Sov. debt crisis	7	5	8	4	37
		After	6	8	8	6	33
	Sovereigns CDS	Pre-crisis	14	15	14	15	2
		Fin. crisis	14	12	13	14	8
		Sov. debt crisis	14	14	12	13	24
		after	13	15	13	13	24
	Sovereigns LTN	Pre-crisis	18	13	19	16	3
		Fin. crisis	17	9	19	13	2
		Sov. debt crisis	18	12	18	16	1
		after	17	12	16	16	6
	Insurers (PDs)	Pre-crisis	7	16	1	13	47
		Fin. crisis	7	22	0	17	45
		Sov. debt crisis	9	18	0	13	37
		after	9	14	0	10	33
	Macro (GDP, ESX, PD-NFC)	Pre-crisis	43	40	38	48	27
		Fin. crisis	42	39	37	51	20
		Sov. debt crisis	41	38	38	48	12
		after	43	37	38	45	4
	Residual	Pre-crisis	10	10	17	1	8
		Fin. crisis	10	16	21	1	2
		Sov. debt crisis	11	14	23	6	2
		after	13	14	24	9	4

Source: Authors' calculations.

1/ Tabulates on the CDS component of "sovereign" in basis points.

98. The following observations can be made based on the analysis:

- Regarding the average PDs, the G-SIBs' PDs peaked during the sovereign debt crisis period and have then decline relatively steeply. Non-G-SIB banks experienced their peak in default risk in the early phase of the crisis, and their PDs have declined less in absolute and relative terms.

- The predominant role in determining bank PDs is played by the macroeconomic (which is an aggregation of three variables) and the sovereign variables. In contrast, banks' contribution to banks' PD dynamics amongst each other are comparably small across groupings as well as over time compared to other factors. This may reflect banks' interconnectedness with other sectors: banks are susceptible to factors outside the banking system, mirroring in turn their role in creating credit for the real sector, investing in sovereign bonds, as well as providing funds to insurers.

- At the onset of the initial phase of the crisis in 2008Q4, non-G-SIBs' rising default risk stemmed from a larger contribution from insurers as their PD rose to 22 percent during the financial crisis. The appreciable contribution of the residual hints at the role of (non-euro area) global factors (not captured by the modeling framework).

- Concerning the contributing factors to changes in insurers' default risk, the two groups (global Group A vs. domestic oriented Group B) exhibit a notable difference with a view to the insurers' own contribution and the residual category: the group of insurers exerts a close to 0 percent contribution to the sub-group of global insurers, and a sizable contribution to domestic insurers (10-17 percent). The residual contribution on the other hand is more sizable for global insurers. The latter finding can be interpreted as meaning that global factors contribute to changes in risk of global insurers.

- Regarding the contributions to sovereign risk (here with respect to CDS only; see last column in Table 19), the bank to sovereign contribution increased markedly in the financial crisis and remained relatively high. The cross-sovereign risk contribution increased markedly with the move into the sovereign debt crisis period (up to 24 percent). The contribution of macroeconomic factors has steadily abated over time.

99. A number of caveats are in order. The CCA- MCS-GVAR model does not fully capture structural changes in risk exposures which have changed for some banks after the crisis. At the same time, because of data limitations, proxies were used when calibrating some sectoral interlinkages (see Appendix I Table 1). The basis for the contribution analysis was a generalized impulse response function concept, that is, the estimates were not based on a structural shock identification method. In comparing the results from the CCA-MCS-GVAR analysis with the findings from the solvency stress tests, it should be noted that market data is not available for some banks, and therefore the solvency stress testing and CCA-MCS-GVAR samples differ. In addition, the former summarizes results using weighted averages, while the CCA- MCS-GVAR uses simple averages.

Appendix I. An Overview of the Structure of the CCA-MCS-GVAR Model

The CCA-MCS-GVAR model system comprises four cross-sections: *N* banks, *M* insurers, *L* sovereigns and a nonfinancial private ("macro") sector covering *F* countries. The variables corresponding to these four cross-sections are denoted $\mathrm{x_i}$, $\mathrm{y_j}$, $\mathrm{z_l}$, and $\mathrm{w_f}$ in the following. All equations contain weighted variable vectors (denoted by an asterisk in the following equations) of the respective own and other cross-sections on the right hand-side of the equations, which are constructed using time-varying weights of different kinds.

$$x_{it} = a_i + \sum_{p_1=1}^{P_1} \Phi_{ip_1}^{x} x_{i,t-p_1} + \sum_{p_2=0}^{P_2} \Lambda_{i,0,p_2} x_{i,t-p_2}^{*,B-B} + \sum_{p_3=0}^{P_3} \Lambda_{i,1,p_3} y_{i,t-p_3}^{*,B-I} + \sum_{p_4=0}^{P_4} \Lambda_{i,2,p_4} z_{i,t-p_4}^{*,B-S} + \sum_{p_5=0}^{P_5} \Lambda_{i,3,p_5} w_{i,t-p_5}^{*,B-M} + \varepsilon_{it}^{x}$$

$$y_{jt} = b_j + \sum_{q_1=1}^{Q_1} \Phi_{jq_1}^{y} y_{j,t-q_1} + \sum_{q_2=0}^{Q_2} \Xi_{j,0,q_2} x_{j,t-q_2}^{*,I-B} + \sum_{q_3=0}^{Q_3} \Xi_{j,1,q_3} y_{j,t-q_3}^{*,I-I} + \sum_{q_4=0}^{Q_4} \Xi_{j,2,q_4} z_{j,t-q_4}^{*,I-S} + \sum_{q_5=0}^{Q_5} \Xi_{j,3,q_5} w_{j,t-q_5}^{*,I-M} + \varepsilon_{jt}^{y}$$

$$z_{lt} = c_l + \sum_{r_1=0}^{R_1} \Phi_{lr_1}^{z} z_{l,t-r_1} + \sum_{r_2=0}^{R_2} \Psi_{l,0,r_2} x_{l,t-r_2}^{*,S-B} + \sum_{r_3=0}^{R_3} \Psi_{l,1,r_3} y_{l,t-r_3}^{*,S-I} + \sum_{r_4=0}^{R_4} \Psi_{l,2,r_4} z_{l,t-r_4}^{*,S-S} + \sum_{r_5=0}^{R_5} \Xi_{l,3,r_5} w_{l,t-r_5}^{*,S-M} + \varepsilon_{lt}^{z}$$

$$w_{ft} = d_f + \sum_{u_1=0}^{U_1} \Phi_{fu_1}^{w} z_{f,t-u_1} + \sum_{u_2=0}^{U_2} \Psi_{f,0,u_2} x_{f,t-u_2}^{*,M-B} + \sum_{u_3=0}^{U_3} \Psi_{f,1,u_3} y_{f,t-u_3}^{*,M-I} + \sum_{u_4=0}^{U_4} \Psi_{f,2,u_4} z_{f,t-u_4}^{*,M-S} + \sum_{u_5=0}^{U_5} \Xi_{f,3,u_5} w_{f,t-u_5}^{*,M-M} + \varepsilon_{ft}^{z}$$

The model in this form has time-contemporaneous relationships, which means that it has to be "solved", for the solved form to not contain such contemporaneous dependence anymore, for the model in turn to be usable for forecasting and impulse response simulations, forecast error variance decompositions, etc.[45]

Chart A summarizes the data that was employed to capture the exposure profiles among banks, insurers, sovereigns and the non-financial private sector, based on which weights are derived to inform the structure of the MCS-GVAR model. All weights are time-varying at a quarterly frequency over the 1999Q1–2017Q4 sample period, except for the Stress Test 2016 (ST2016) database which contains cross-country loan exposure profiles as of end-2015.

[45] The details concerning the solution method can be found in Gross, M., Kok, C. and D. Zochowski, 2016, "The impact of bank capital on economic activity – Evidence from a Mixed-Cross-Section GVAR model". ECB Working Paper No. 1888.

Appendix I Table 1. Euro Area: Sources of Exposure Data for Banks, Insurers, Sovereigns, and the Private Sector

LHS in model (asset side on BS; holder)	RHS in model (liability side on BS; issuer): Banks (B)	Insurers (I)	Sovereigns (S)	NFC/Macro (M)
Banks (B)	SHSG and ST2016 (financial institutions exp., not issuer specific)	SHSG	SHSG and ST2016 (sovereign banking book exp., issuer specific)	SHSG and ST 2016 (private sector loan exposures, country-specific)
Insurers (I)	SHSS	SHSS	SHSS	SHSS
Sovereigns (S)	SHSS	SHSS	SHSS	Unit-linked (each country to its own sovereign)
NFC/Macro (M)	Transpose of B-M weights	SHSS	SHSS	Bilateral trade flows

Note: SHSG abbreviates Securities Holdings Statistics (Group level, available for individual banks). SHSS abbreviates the Securities Holdings Statistics (Sector level). Macro (M): this label denotes the nonfinancial private sector, i.e. nonfinancial corporations and households.

Appendix II. List of Banks, Insurers, and Countries

Appendix II Table 1. Banks

#	loc.	ISIN	Firm (short name)	Grouping 1: geo focus	Grouping 2: G-SIB
B1	AT	AT000060306	Raiffeisen Bank	Domestic	Non-G-SIB
B2	AT	AT0000652011	Erste Group	Europe	Non-G-SIB
B3	BE	BE0003565737	KBC	Europe	Non-G-SIB
B4	DE	DE0005140008	Deutsche Bank	Global	G-SIB
B5	DE	DE000CBK1001	Commerzbank	Europe	Non-G-SIB
B6	ES	ES0113211835	BBVA	Global	Non-G-SIB
B7	ES	ES0113307062	Bankia	Domestic	Non-G-SIB
B8	ES	ES0113679137	Bankinter	Domestic	Non-G-SIB
B9	ES	ES0113860A34	Sabadell	Domestic	Non-G-SIB
B10	ES	ES0113900J37	Santander	Global	G-SIB
B11	ES	ES0140609019	CaixaBank	Domestic	Non-G-SIB
B12	FI	FI0009003222	Pohjola	Domestic	Non-G-SIB
B13	FR	FR0000045072	Crédit Agricole	Europe	G-SIB
B14	FR	FR0000120685	Natixis	Global	Non-G-SIB
B15	FR	FR0000130809	Société Générale	Europe	G-SIB
B16	FR	FR0000131104	BNP	Europe	G-SIB
B17	FR	FR0005025004	CMU	Global	Non-G-SIB
B18	IE	IE0030606259	Bank of Ireland	Domestic	Non-G-SIB
B19	IE	IE00BYSZ9G33	Allied Irish Banks	Domestic	Non-G-SIB
B20	IT	IT000006259	Mediobanca	Domestic	Non-G-SIB
B21	IT	IT0000066123	BPER	Domestic	Non-G-SIB
B22	IT	IT0000072618	Intesa Sanpaolo	Domestic	Non-G-SIB
B23	IT	IT0003487029	UBI	Domestic	Non-G-SIB
B24	IT	IT0005218380	BPM	Domestic	Non-G-SIB
B25	IT	IT0005218752	Monte dei Paschi	Domestic	Non-G-SIB
B26	IT	IT0005239360	UniCredit	Europe	G-SIB
B27	NL	NL0000301109	ABN Amro	Global	Non-G-SIB
B28	NL	NL0011821202	ING	Europe	G-SIB
B29	NL	NL0000390706	SNS Reaal	Domestic	Non-G-SIB
B30	PT	PTCP0AM0015	BCP	Domestic	Non-G-SIB

Appendix II Table 2. Insurers

#	loc.	ISIN	Firm (short name)	Grouping
I1	AT	AT0000908504	VIENNA INSURANCE GROUP	Domestic
I2	DE	DE0008404005	ALLIANZ SE	Global
I3	DE	DE0008400029	GENERALI DEUTSCHLAND HOLDING AG	Domestic
I4	DE	DE0008430026	MUENCHENER RUECKVERSICHERUNGS GESELLSCHAFT AG IN MUENCHEN	Global
I5	FR	FR0000120628	AXA SA	Global
I6	FR	FR0000120222	CNP ASSURANCES	Domestic
I7	FR	FR0010411983	SCOR SE	Global
I8	IT	IT0000062072	ASSICURAZIONI GENERALI SPA	Global
I9	IT	IT0004810054	UNIPOL GRUPPO SPA	Domestic
I10	NL	NL0000303709	AEGON N.V.	Global
I11	NL	NL0009294552	DELTA LLOYD NV	Domestic

Appendix II Table 3. Countries

# sov	# macro	ISO	Country
S1	M1	AT	Austria
S2	M2	BE	Belgium
S3	M3	CY	Cyprus
S4	M4	DE	Germany
S5	M5	ES	Spain
S6	M6	FR	France
S7	M7	GR	Greece
S8	M8	IE	Ireland
S9	M9	IT	Italy
S10	M10	NL	Netherlands
S11	M11	PT	Portugal
S12	M12	EE	Estonia
S13	M13	FI	Finland
S14	M14	LT	Lithuania
S15	M15	LU	Luxembourg
S16	M16	LV	Latvia
S17	M17	MT	Malta
S18	M18	SI	Slovenia
S19	M19	SK	Slovakia

DATA GAPS IN THE NONBANK, NON-INSURANCE FINANCIAL SECTOR[46]

Data gaps in the NBNI segment of the financial sector may hinder comprehensive monitoring and appraisal of risks. Major strides have been made, but a sizeable gap remains, and needs to be closed swiftly.

100. There are important data gaps confronting the measurement of certain segments of the NBNI financial sector. Specifically, a key gap is the other financial institutions (OFI) residual. The OFI residual is the difference between the total assets of the financial system and the assets held by all known subsectors (banks, insurance corporations and pension funds, financial vehicle corporations (FVCs), FCLs, investment funds, and MMFs). It includes financial institutions such as broker-dealers, venture capital funds, leasing and factoring companies, as well as special purpose vehicles not engaged in securitization (Table 20).

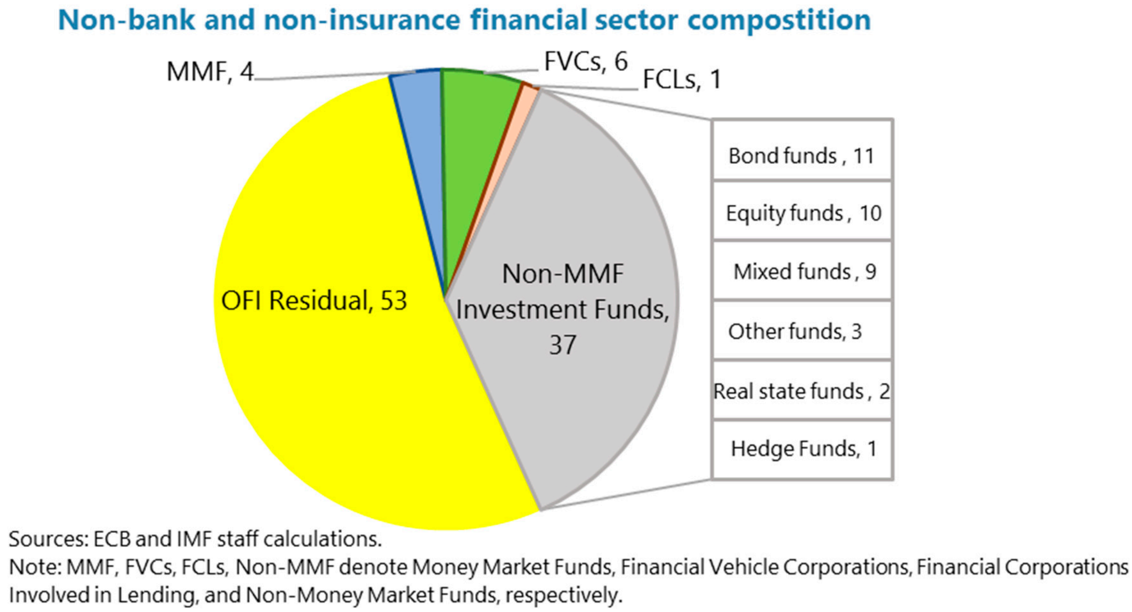
101. The euro area OFI residual is sizeable. In mid-2017, the residual accounted for €17 trillion, 22 percent of total financial system assets, 53 percent of the NBNI financial sector, and 153 percent of GDP (Figure 24). Data challenges arise owing to several factors. For example, national accounts statistics are based on residency, and therefore omit some cross-border activities, such as the operations of off-shore funds managed by euro area companies. Hence, OFI residual at the euro area level exceeds the aggregate of country-level OFI residuals. The latter benefit from supervisory and other non-public national data sources allowing more granular entity classification (see the 2017 ESRB Shadow Banking Monitor for further details).

102. These data gaps limit the comprehensive monitoring and assessment of risks associated with the euro area NBNI sector. Risks tend to center around entities engaged in credit intermediation, liquidity transformation or financial leverage. Even in cases where an entity does not partake in such activities, it may still be a part of a financial intermediation chain, for instance, if it creates leverage synthetically via derivatives or provides guarantees. However, in some countries, sector-specific risks may be lower because the residual includes many captive institutions such as holding companies or special purpose entities that raise funds to be used by their parents. These entities can be either within the supervisory perimeter (for example, as a financial institution within a holding structure) or they may facilitate intra-group transaction or fiscally-oriented operations by non-financial corporations.

103. In sum, although major strides have been made, the data gaps in the NBNI sector remain sizeable and should be closed expeditiously. A cross-country consistent and granular view of the entities populating the OFI sector would facilitate the tracking and appraisal of risks and thereby inform appropriate and customized policy responses that foster euro area financial stability.

[46] This chapter was prepared by Selim Elekdag, Tadeusz Galeza, and Sheheryar Malik, all Monetary and Capital Markets Department, IMF.

Figure 24. Euro Area: Data Gaps in the Nonbank, Non-Insurance Financial Sector 1/



Sources: ECB, and IMF staff calculations.

1/ as of 2017Q2

Table 20. Euro Area: The Nonbank, Non-Insurance Financial Sector 1/

Entity	Assets (Share of the total financial system assets, percent)
Nonbank, non-insurance financial sector	41.3
Investment funds	16.9
Money market funds (MMFs)	1.5
Investment funds	15.4
Bond funds	4.6
Equity funds	4.1
Mixed funds	3.9
Real estate funds	0.9
Hedge funds	0.6
Other funds 2/	1.3
Other financial institutions (OFI)	24.4
Financial vehicle corporations (FVCs) 3/	2.4
Financial corporations engaged in lending (FCLs) 4/	0.6
OFI residual	21.4
Securities and derivative dealers (SDDs) 5/	
Specialist financial corporations (SFCs) 6/	
Financial auxiliaries 7/	
Captive-financial institutions and money lenders 8/	

Sources: ECB, and IMF staff calculations.

1/ as of 2017Q2
2/ Includes private equity and exchange-traded funds
3/ Special purpose entities (SPEs) engaged in securitization
4/ Includes leasing and factoring companies
5/ Includes broker-dealers
6/ Includes venture capital funds
7/ Includes insurance and loan brokers, payment institutions
8/ Include SPEs not engaged in securitization, holding companies