Journal of Banking and Finance 120 (2020) 105949

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Breaking the Bank? A Probabilistic Assessment of Euro Area Bank Profitability☆

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ARTICLE INFO

Article history:
Received 3 January 2020
Accepted 31 August 2020
Available online 3 September 2020

JEL Classification:
C32
E30
G01
G21

Keywords:
Bank profitability
Quantile regressions
Conditional distributions

ABSTRACT

This paper explores the determinants of profitability across large euro area banks using an approach based on conditional profitability distributions. The most reliable determinants of bank profitability are real GDP growth and the nonperforming loan (NPL) ratio. The estimated conditional distributions reveal that, while higher growth would raise profits on average, a large swath of banks would most likely continue to struggle even amid a strong economic recovery. Therefore, for some banks, a determined reduction in NPLs combined with cost efficiency improvements and customized changes to their business models appears to be the most promising strategy for durably raising profitability.

1. Introduction

During the past decade, European banks have been chronically less profitable than their peers in the United States.[1] Fig. 1 shows the median return on equity (ROE) for a broad sample of euro area and U.S. banks over the 2005-2019 period. As illustrated in this figure, bank profitability declined in tandem across both financial systems from a peak ROE level of 12% in 2005 to about 5% in 2009 with the intensification of the Global Financial Crisis (GFC). However, although U.S. banks' profitability recovered over the post-crisis period, euro area banks continued to suffer from low profitability.

Focusing on large euro area banks, this paper reveals that persistently weak bank profitability is especially prevalent for a "tail" of weak performers. In particular, Fig. 2 depicts two key headline profitability measures—return on assets (ROA) and ROE—using a balanced sample of large euro area banks (to help address, inter alia, survivorship bias). As shown in this figure, the ROA and ROE of many euro area banks declined substantially after the GFC and have remained at low levels ever since, even after accounting for lower interest rates. Importantly, the occurrence of negative ROA and ROE is notable—and especially prevalent during the European debt crisis—indicating that weak profitability is an acute concern for some euro area banks. Moreover, forecasts by market analysts suggest that many banks' ROE levels will most likely remain below 8% in coming years, which would likely continue to act as a drag on bank share prices.[2]

Banks' persistently weak profitability is a systemic financial stability concern in the euro area. Banks may have ample capital to cushion against shocks, but need profits to (re-) build buffers by retaining earnings or attracting new capital. Moreover, low profitability may inhibit proactively addressing impaired assets, as write-downs could further erode earnings. In addition, weaker profitability could foster undue risk-taking aimed at generating higher returns (gambling for resurrection), which would heighten systemic risk. Importantly, weak profits could also potentially force banks to reduce assets and thereby hamper credit intermediation to the real economy. These concerns continue to apply to many European banks.

☆ The views expressed in this working paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

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[1] The lagging profitability of European banks relative to their U.S. counterparts is not a new issue. In fact, Berger and others (2000) find that U.S. banks are better able to operate efficiently across borders relative to banks headquartered in other major financial jurisdictions. As an example of a recent comparative study, see Feng and Wang (2018).

[2] The 8% ROE threshold is based on pre-COVID-19 investor surveys suggesting that banks' cost of equity—with all the standard caveats about its measurement—is currently about 8–10% (See *Global Financial Stability Report* (IMF, 2017a) and ECB, 2019).

https://doi.org/10.1016/j.jbankfin.2020.105949
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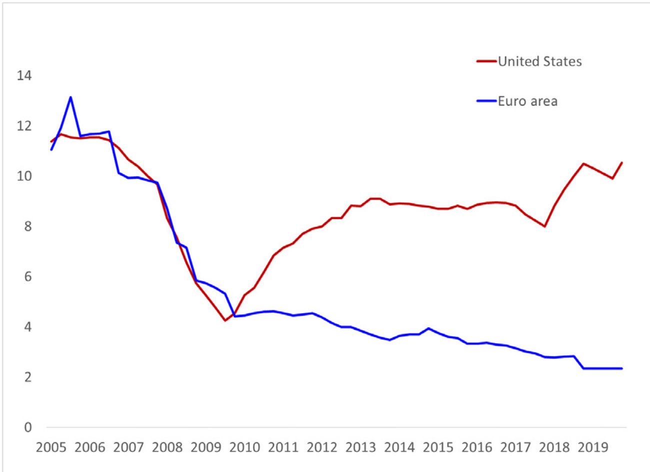

Fig. 1. Bank Profitability: Euro Area and U.S. Banks (Median return on equity; in%). *Source:* IMF (2020).

There is an active debate in both policy circles and academia on the relative importance of different drivers of bank profitability. Most papers acknowledge that a variety of bank-specific, cyclical, and structural factors drive profitability.[3] One side of the debate argues that cyclical factors, including growth, are dominant (see Kok, More, and Pancaro, 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 conditions, but highlights the importance of structural factors (see, for example, Demirgüç-Kunt and Huizinga, 1999; Dietrich and Wanzenried, 2011; IMF, 2017; and Detragiache, Tressel, and Turk-Ariss, 2018; IMF, 2018).[4]

Much of the related literature focuses on average profitability dynamics across banking systems. Even when using a panel of diverse banks, these papers report how selected determinants affect bank profitability on average. Yet, this practice could misinform policymakers, especially when considering a very heterogeneous banking system such as that in the euro area. For instance, although the average profitability across banks would most likely increase amid an economic upswing, this increase in profitability may be predominantly driven by banks with sound balance sheets. In contrast, a large share of banks with weaker balance sheets may not be in a position to benefit from stronger economic growth. Therefore, focusing only on the soundness of banks on average would mask the deeper structural problems concentrated in the weaker tail of the bank profitability distribution.

To fill this gap in the literature, this paper proposes a probabilistic approach, which places greater emphasis on bank heterogeneity by focusing on bank profitability *distributions*. Accordingly, several related questions form the structure of the paper: 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*?

Focusing on large euro area banks, this paper addresses these questions using an empirical approach. First, to lay the groundwork, 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," SIs), which are under the supervisory perimeter of the Single Supervisory Mechanism (SSM).

Second, in the more innovative part of the paper, quantile regressions are used to generate *profitability distributions* that are 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 that goes beyond standard comparative statics centered on averages. Importantly, this 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. Specifically, comparative static exercises are conducted to quantify the likelihood of ROE remaining below 8% in response to changes to higher GDP growth, or lower NPL ratios.

The main results of the paper can be summarized as follows:

First, the most robust determinants of bank profitability across large euro area banks appear to be real GDP growth and the NPL ratio. An increase in the growth rate of one percentage point is associated with a 15–35 basis point rise in ROA, which is considerable, given that average ROA across banks over 2007–2016 was 34 basis points. There is some evidence suggesting that growth boosts bank profits mainly by reducing loan loss provisions and, to a lesser extent, enhancing non-interest income. A decline of one percentage point in the NPL ratio can lift ROA by about 4–9 basis points.[5] Findings suggest that a higher stock of NPLs is associated with higher servicing costs tied to impaired loans, which represent an additional drag on bank profitability.

Second, 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 the period 2007–2016. Estimates suggest that, under the baseline, the likelihood of a (representative) bank's ROE falling below 8% remains elevated at 83%, ceteris paribus. A hypothetical scenario indicates that raising growth by one standard deviation (that is, 3.3percentage points) reduces this likelihood by 21 percentage points. However, even though average bank profitability increases, the probability of ROE coming in below 8% is still substantial.

Third, under a scenario with higher growth and a lower NPL ratio, however, the probability of a representative bank having an ROE less than 8% now declines to 49%, a difference of 33 percentage points relative to the baseline. Importantly, the joint materialization of higher growth and lower NPLs reduces the probability of ROE falling below 8% more than these shocks considered individually (reflecting nonlinear interactions). This scenario could be interpreted as demonstrating the benefits of an aggressive NPL reduction in the context of a robust economic upswing.

Additional results suggest that lower cost-to-income ratios are associated with higher profitability for banks outside of the weakest end of the profitability spectrum, but the results on business models and market concentration are more mixed. Moreover, it is difficult to identify whether higher short-term interest rates and a steeper yield curve would generally raise ROA or ROE; there are

[3] Recent studies include Alessandri and Nelson (2015); Borio, Gambacorta, Hofmann (2017); Demirgüç-Kunt and Huizinga (2010); Detragiache, Tressel, and Turk-Ariss (2018); Dietrich and Wanzenried (2011); Gambacorta and others (2014); Kok, More, and Pancaro (2015); Mirzaei, Moore, and Liu (2013); and Shehzad, De Haan, and Scholtens (2013).

[4] There is a vast literature on the role of market structure and banking-system concentration that can be traced back to at least the work of Short (1979). Recent studies also emphasize other cyclical determinants of bank profitability, including financial and monetary conditions (Borio, Gambacorta, and Hofmann, 2017; Detragiache, Tressel, and Turk-Ariss, 2018).

[5] The semi-elasticity on the NPL ratio is smaller than that on GDP growth, but NPL ratios are much higher and more variable than GDP growth rates.

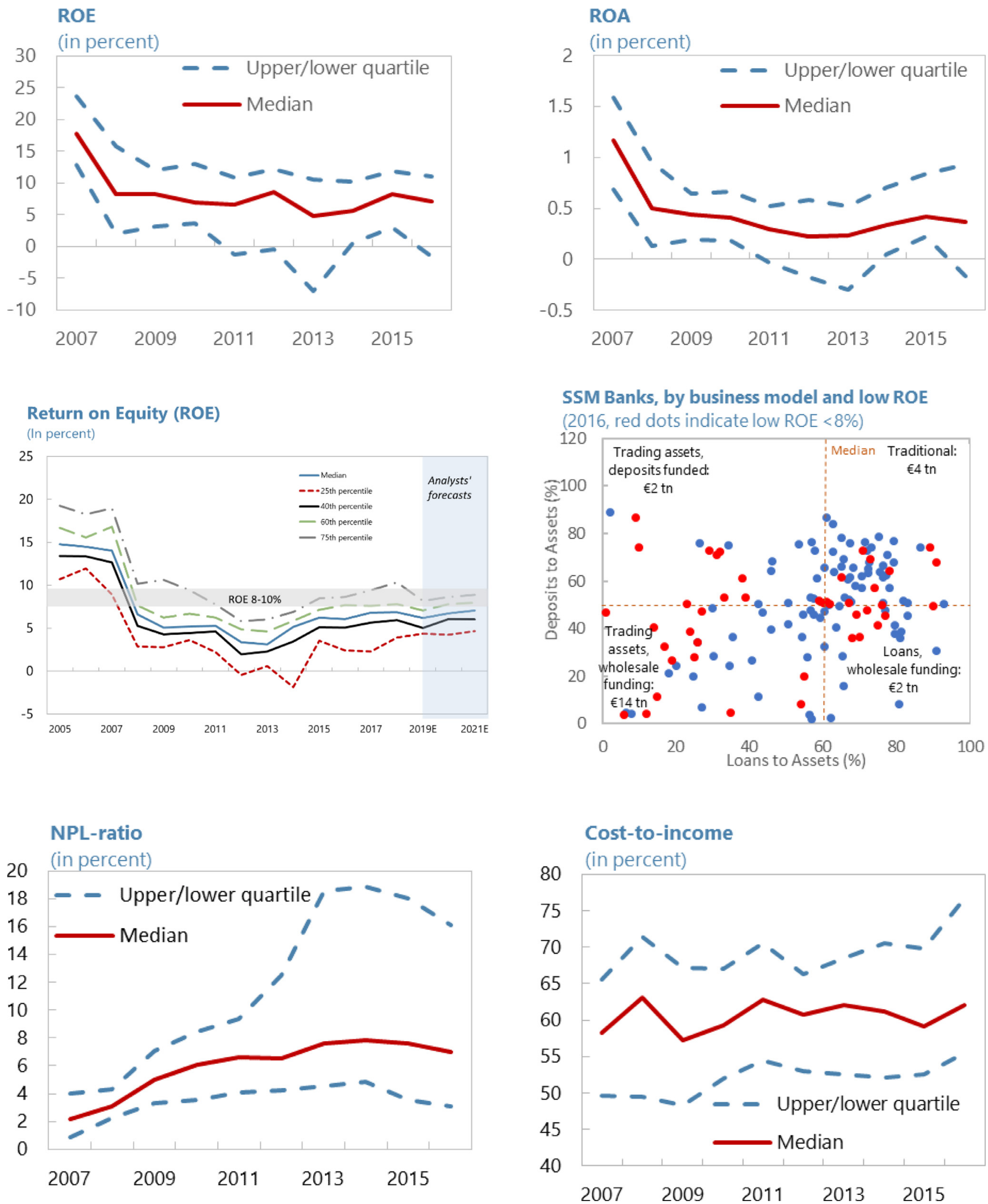

Fig. 2. Euro Area Banks ("Significant Institutions"): Key Trends and Stylized Facts. *Sources:* Bloomberg Finance L.P., Fitch Connect, and authors' calculations. Notes: Based on a balanced sample of 45 SSM (Single Supervisory Mechanism) banks over 2007–2016, with 56% of end-2016 SSM assets. Cost of equity estimates, ranging from 8–10%, are subject to various caveats, including with regard to measurement.

counterbalancing effects which may differ across banks depending on their business models.

A key takeaway is that an economic recovery alone will likely be insufficient to resolve many banks' enduring profitability challenges. For some banks in particular, a determined reduction in NPLs, combined with improvements in cost efficiency, holds the most promise in durably raising profitability. Such a strategy stands to also benefit from a customized approach to revising individual bank business models.

In addition to the selected literature reviewed in the next section, several studies that relate to our paper also have used quantile regression analysis to investigate banking performance. In earlier work, Wheelock and Wilson (2009), develop a quantile estimator to examine changes in the efficiency and productivity of U.S. banks. They find that although U.S. banks have generally become more efficient, only large banks—those with at least $1 billion of total assets—experienced significant productivity improvements. This, they argue, is consistent with the view that rapid advances in information technology have disproportionately benefited larger banks. Likewise, Koutsomanoli-Filippaki and Mamatzakis (2011) study bank cost efficiency in the European context over 2000–2005. Focusing on U.K. banks, de-Ramon, Francis, and Straughan (2019) use quantile regression analysis to assess how industry-wide competition differentially affects bank-level measures of risk. Interestingly, they find that risk increases as competition intensifies for the most stable firms, but that risk is lower amid stronger competition for more fragile firms. Li (2010) examines the risk—return relationship for listed U.S. banks and finds that a positive risk-return relationship is present for the profitable banks, but there is a negative relationship for less profitable banks. More recently, Lang and Forletta (2019) investigate how measures of systemic risk affect European banks' ROA. Building on the work of Adrian, Boyarchenko, and Giannone (2019), they find that elevated levels of cyclical systemic risk increase the downside risks to bank-level ROA three to five years ahead.

In contrast to this rich literature, our paper focuses on how selected determinants differentially influence the *distribution* of euro area bank profitability. Moreover, our paper uses the quantile regression estimates to generate these profitability distributions—a second step that departs from many other papers. Importantly, these profitability distributions allow for comparative static exercises which clearly visualize—and presumably more effectively communicate—how stylized shocks to the underlying determinants affect the shape of the profitability distribution. Specifically, in our paper, we can illustrate how under a scenario of higher growth, a sizeable share of banks would remain in the weaker left tail of the distribution even though average profitability has increased.

2. Conceptual and empirical framework

This section begins with a selected review of the literature on the determinants of bank profitability and provides an overview of the econometric framework. It then discusses the generation of bank profitability distributions conditional on selected determinants.

2.1. Conceptual framework

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 inclusion, and previous empirical results on their relevance are discussed in this section. In many cases, the theoretical impact of these determinants on profitability remains inconclusive, which further motivates our empirical investigation.

2.1.1. Bank-specific determinants

Bank-specific determinants of profitability can be split into two broad categories. The first encompasses financial soundness indicators such as solvency and asset quality, while the second category covers measures of size, efficiency, diversification, and business models. The set of bank-specific determinants are generally similar across many empirical studies and are summarized below.

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 possibility of bankruptcy, thus supporting earnings (Demirgüç-Kunt and Huizinga, 1999; Detragiache, Tressel, and Turk-Ariss, 2018). 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 with the hope that greater earnings will restore solvency (this has been referred to as "gambling for resurrection"; see Akerlof and others, 1993; Freixas, Parigi, and Rochet, 2004, Hellmann, Murdock, and Stiglitz, 2000; and IMF, 2014).[6]

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 that take on greater risk tend to eventually incur higher losses, which reduce returns. Empirical evidence suggests that higher credit risk (proxied with NPL and loan-loss provisioning ratios) is characterized by lower profitability (Altavilla, Boucinha, and Pedyro, 2018; Bikker and Hu, 2002; Detragiache, Tressel, and Turk-Ariss, 2018). For instance, elevated stocks of NPLs can be problematic because they create uncertainty regarding the quality and valuation of assets, thereby potentially rendering funding more expensive, among other things.[7] In addition, NPLs can act as a drag on pre-provision earnings by increasing operational and legal costs.[8] In sum, the econometric analysis uses the NPL ratio as an explanatory variable. Recognizing that this ratio is not independent of macroeconomic factors, we initially consider the lagged NPL ratio. Moreover, we also use the change in the NPL ratio which, in contrast to the stock, is more likely to be influenced by GDP growth and other macroeconomic conditions (please see Section 4 for further details).

Size: Controlling for bank size is important, but its relation to profitability is not conclusive (Shehzad, De Haan, and Scholtens 2013). Some studies argue that larger banks bene-

[6] 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. Laeven and Levine (2009) emphasize the importance of bank risk taking and corporate governance structures.

[7] It should be noted that banks may not recognize and/or write-off delinquent loans as soon as they are apparent, which would overstate the soundness of their balance sheets (for example, assets and equity). In fact, in terms of motivation, the new IFRS 9 impairment model is intended to address a criticism of the impairment model used during the financial crisis (that it allowed banks to delay recognition of asset impairments).

[8] In particular, NPLs need to be handled by potentially sizable teams of specialized staff, and the workout process can be timely. In addition, NPLs do not generate interest income, and owing to higher risk weights, they can hold back lending (see, for example, Baudina and Yun 2017). Note also that NPL reduction would entail capital costs when the price of such NPLs is below book value or if NPLs have to be written off (against capital). At the same time, net loans and, hence, total assets would also fall if NPLs are written off. Given that it is a priori unclear how such changes to the NPL ratio would affect bank capital, the regressions include the equity-to-assets ratio. See also Altunbas, Manganelli, and Marquez-Ibanez (2011) and Xu, Hu, and Das (2019).

fit from economies of scale, thereby enhancing the bottom line (Berger 1995; Goddard, Molyneux, and Wilson 2004). In contrast, other studies claim that larger banks suffer from diseconomies of scale, reflecting agency, overhead, and managerial costs (Tregenna 2009).

Efficiency: Better operating efficiency is typically associated with greater bank profitability (Detragiache, Tressel, and Turk-Ariss 2018; Dietrich and Wanzenried 2011; Molyneux and Thornton 1992). Standard measures include cost-to-income or cost-to-assets ratios, occasionally differentiating between personnel and non-personnel costs (Demirgüç-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 (Demirgüç-Kunt and Huizinga 2010; Gambacorta and others 2014; Valverde and Fernández 2007), while others find a negative link as a higher share of non-interest income is associated with more volatile earnings (Kok and others 2016; Stiroh 2004).

Business models: It is also important to consider banks' diverse business models (Demirgüç-Kunt and Huizinga 2010; Kok, More, and Petrescu 2016; Detragiache, Tressel, and Turk-Ariss 2018; Valverde and Fernández 2007). 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; IMF 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.[9]

2.1.2. Cyclical determinants

Accounting for the macroeconomic environment is standard practice, and many studies find that profitability is procyclical (for example, Albertazzi and Gambacorta 2009). An economic expansion will increase the demand for intermediation services (including lending and underwriting and advisory services), thereby lifting net interest income, fees, and commissions. In addition, improving asset quality will reduce the need for loan loss provisioning and thus contribute to profitability.

Other cyclical factors can also influence banks' profitability. For instance, many of the aforementioned studies control for (short-term) policy rates, longer-term interest rates, or the slope of the yield curve. Although conventional wisdom suggests that a steeper yield curve would boost profitability by improving bank income margins, higher long-term interest rates can also reduce the valuation of longer-term securities (Alessandri and Nelson 2015; Borio, Gambacorta, and Hofmann 2017). The impact of short-term interest rates on profitability is even more ambiguous given the differing presence of loan-pricing frictions across banks. The impact on bank profits is estimated to be positive in Demirgüç-Kunt and Huizinga (1999), negative by Alessandri and Nelson (2015), and insignificant by Albertazzi and Gambacorta (2009). More recently, Altavilla, Boucinha, and Pedyro (2018) argue that monetary easing (a decrease in the short-term interest rate and/or a flattening of the yield curve) is not associated with lower bank profits.

Given the turbulent market conditions witnessed over the past decade, it is important to control for financial conditions more broadly. To this end, a new euro area financial conditions index (FCI) was used, which includes measures of spreads and volatility that tend to spike during episodes of acute market distress (for details, see Arregui and others 2018). As emphasized in Adrian, Boyarchenko, Giannone (2019), tighter FCI outturns are associated with a higher likelihood of future recessions. Another benefit of including FCIs is that they include real estate prices, which may be particularly relevant 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 sake of brevity).

It is also important to account for major crisis periods to ensure such shocks are not driving the results. Hence, in the baseline and most other specifications, time fixed effects are included to capture regional and global developments that may affect banks' profitability.

2.1.3. Structural and other determinants

Investigating the role of market structure can be traced at least to the work of Short (1979). Market concentration measures are 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.[10] Other potential structural determinants including ownership, governance, and supervisory regimes could also affect banks' performance, however, they are not considered in this study due to data limitations.[11]

2.2. Econometric Approach

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:

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

where $y_{b,\,c,\,t}$ denotes the headline profitability measures (ROA, ROE) and relevant income and cost components (for example, net interest income/assets, non-interest income/assets, costs/assets) for bank b, in country c, in year t; the vectors $X_{b,c,t-1}$, $Z_{c,\,t}$, and $W_{c,\,t}$ encompass the bank-specific, cyclical, and structural determinants; $Other_{b,\,c,\,t}$ includes (bank and time) fixed effects and a residual term. 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.

2.3. Conditional profitability distributions

The more innovative aspect of this paper 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

[9] 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.

[10] For example, see Berger (1995), Berger and others (2000), Bourke (1989), Molyneux, and Thornton (1992), Tregenna (2009), and Mirzaei, Moore, and Liu (2013). 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 (Erel, 2011) and suboptimal credit volumes. 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 the impact of size and concentration on profitability are related.

[11] For example, even the updated supervisory indicators by Barth, Caprio, and Levine (2006) end in 2011. Likewise, more recent studies such as Barth and others (2013) use data up to 2007. Data coverage also limits the inclusion of indicators that could capture quasi-public competitors and nonbank competition. The governance indicators used by Laeven and Levine (2009) are only available for a single year. Demirgüç-Kunt and Huizinga (1999) also consider the role of the strength of institutions (using, for example, proxies such as law and order indexes).

reviewed above. Selected determinants can then be shocked to assess how the shape of the profitability distribution changes—an approach that 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.

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

$$y^q_{b,c,t} = \beta^q \Xi_{b,c,t} + \epsilon^q_t \tag{2}$$

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 various percentiles of interest, for example, $q = \{0.05;\ 0.25;\ 0.50;\ 0.75;\ 0.95\}$, respectively. 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.

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 a smoothing of the quantile function. In line with the approach of Adrian, Boyarchenko, and Giannone (2019), this is accomplished via fitting a (parametric form) "skewed" t-distribution:

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

where $g(z) = \ \bar{g}(z;\ \nu)/s$, with $\bar{g}(.)$ denoting the PDF of standard Student-t with ν 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 Fernandez and Steel (2012), further explored and refined in Giot and Laurent (2003) and Lambert and Laurent (2002); see also Boudt, Peterson, and Croux (2009).[12] For specified values for the conditioning variables, the four parameters $\{\mu,\ s,\ \nu,\xi\}$ of the implied density are pinned down by minimizing the squared distance between the estimated quantile function, $\hat{y}^q$, and theoretical quantile function $y^{q,f}(\mu,\ s,\ \nu,\xi)$ corresponding to the above skewed-t distribution. Specifically, the 5[th], 25[th], 50[th], 75[th], and 95[th] percentiles, for example, can be matched via distance minimization:

$$\{\mu,s,\nu,\xi\} = {}^{\text{argmin}}_{\mu,s,\nu,\xi} \sum_q \left\{\hat{y}^q - y^{q,f}(\mu,s,\nu,\xi)\right\}^2 \tag{4}$$

where $\mu \in$ R, $s > 0$, $\nu \geq 2$ 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 $\nu \to \infty$, $f(y;\ \mu,\ s,\ \nu,\ \xi)$ is characterized by tail properties resembling a Gaussian; moreover, the density is symmetric when $\xi = 1$.

3. Data, key trends, and stylized facts

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

3.1. Data

Data on large euro area banks is collected from publicly available sources. Balance sheet and income statement information from the Fitch Connect database over 2007–2016 are complemented with country-level macroeconomic data and various structural indicators.[13] 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).[14]

It is important to recognize several features of the data that 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, creating survivorship bias. Third, some banks have sizeable international operations, and are thus influenced by global macroeconomic 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.

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 for banks with significant exposures beyond the euro area or under turbulent market conditions. Second, as a robustness check, the regressions are re-estimated using a balanced sample of banks. Third, quantile regressions, which are less sensitive to outliers, are undertaken for comparison. The baseline specifications are also complemented by an array of robustness checks.

3.2. Key Trends and Stylized Facts

Average profitability has been on a downtrend since 2007, but there is wide variation among banks. Therefore, to assess key trends more accurately, a balanced sample of 45 SSM-supervised significant institutions (SSM SIs), accounting for 56% of sample assets in 2016, is used.[15] Fig. 2 displays the median, 25[th] and 75[th] 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. By 2017Q4, ROE was about 6% on average across all SIs.

Table 2 summarizes some stylized facts that reinforce the concerns associated with euro area bank profitability. The ROA outturn for 2016, at 0.34%, 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 differences in leverage (the inverse of Equity/Assets) could make a significant difference in ROE.

Low profitability is pervasive across bank business models. A scatterplot of SSM banks against two indicators—loans-to-assets

[12] Alternative specifications for the skewed t-distribution are present in literature, for example, by Azzalini and Capitanio (2003) and Hansen (1994). These are essentially equivalent given a (nonlinear) transformation of the skewness parameter.

[13] The main advantage of the Fitch Connect database is that its coverage of banks goes beyond the listed universe and thereby includes privately held banks, which is particularly relevant in the European context.

[14] Note that euro area banking system assets were about €25 trillion at end-2017 (based on consolidated banking data). Consolidated SSM-supervised banks include foreign subsidiaries, which matter for the consolidated entities' profitability, balance sheet soundness, and ability to provide credit to the euro area economy.

[15] A balanced sample help address any potential concerns associated with survivorship bias and, relatedly, mergers and acquisitions.

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

Bank		Total Assets	Bank		Total Assets
Erste Group Bank AG	AT	217.5	Bank of Ireland	IE	142.6
Raiffeisen Bank International AG	AT	124.6	Allied Irish Banks, Plc	IE	112.3
BAWAG Holding GmbH	AT	38.9	Ulster Bank Ireland, DAC	IE	33.8
Sberbank Europe AG	AT	15.6	Citibank Europe, Plc	IE	24.0
Volksbank Wien AG	AT	10.9	UniCredit S.p.A.	IT	936.8
VTB Bank (Austria) AG	AT	9.2	Intesa Sanpaolo S.p.A.	IT	736.5
KBC Group NV	BE	274.7	Banco BPM S.p.A.	IT	186.6
Dexia	BE	250.7	Banca Monte dei Paschi di Siena S.p.A.	IT	184.0
Belfius Bank SA/NV	BE	192.7	Unione di Banche Italiane S.p.A.	IT	127.6
Argenta B.V.G. NV	BE	43.3	Mediobanca S.p.a.	IT	79.1
Bank of New York Mellon S.A./N.V.	BE	38.6	BPER Banca S.p.A.	IT	66.7
AXA Bank Europe	BE	33.7	Iccrea Holding S.p.A.	IT	53.0
Bank of Cyprus Public Company Limited	CY	25.3	Banca Popolare di Vicenza	IT	43.3
Cooperative Central Bank Ltd.	CY	15.5	Credito Emiliano S.p.A.	IT	40.8
RCB Bank Ltd	CY	14.6	Banca Popolare di Sondrio-Societa' Cooperativa per Azioni	IT	38.7
Hellenic Bank Public Company Limited	CY	8.1	Veneto Banca S.p.A.	IT	36.3
Swedbank AS	EE	10.5	Banca Carige S.p.A. - Cassa di Risparmio di Genova e Imperia	IT	33.0
AS SEB Pank	EE	5.7	Swedbank AS (Latvia)	LV	5.9
Nordea Bank Finland Plc	FI	328.4	ABLV Bank A.S.	LV	5.4
OP Financial Group	FI	135.5	AS SEB Banka	LV	3.9
Danske Bank PLC	FI	33.0	Banque et Caisse d'Epargne de l'Etat	LU	46.6
BNP Paribas S.A.	FR	2171.1	Precision Capital S.A.	LU	35.6
Credit Agricole	FR	1849.6	JP Morgan Bank Luxembourg S.A.	LU	11.3
Credit Mutuel	FR	805.5	HSBC Bank Malta, Plc	MT	7.9
BPCE S.A.	FR	788.4	ING Group	NL	1094.4
La Banque Postale	FR	238.1	Cooperatieve Rabobank U.A.	NL	739.1
HSBC France	FR	183.4	ABN AMRO Group N.V.	NL	443.5
SFIL	FR	91.1	Bank Nederlandse Gemeenten (BNG)	NL	162.8
Bpifrance Financement S.A.	FR	48.6	Nederlandse Waterschapsbank N.V.	NL	99.4
Caisse de Refinancement de l'Habitat (CRH)	FR	46.4	de Volksbank N.V.	NL	68.3
RCI Banque	FR	40.4	Caixa Geral de Depositos, S.A.	PT	109.9
Agence Francaise de Developpement (AFD)	FR	39.0	Banco Comercial Portugues, S.A.	PT	81.5
Barclays France SA	FR	0.0	Novo Banco, S.A.	PT	62.6
Deutsche Bank AG	DE	1773.7	Slovenska Sporitelna	SK	15.2
Commerzbank AG	DE	580.0	Vseobecna Uverova Banka	SK	13.7
DZ BANK AG Deutsche Zentral-Genossenschaftsbank	DE	444.6	Tatra Banka	SK	12.2
Landesbank Baden-Wuerttemberg	DE	254.8	Nova Ljubljanska banka d.d.	SI	12.9
Bayerische Landesbank	DE	234.9	Abanka d.d.	SI	4.2
Norddeutsche Landesbank Girozentrale	DE	197.1	Banco Santander, S.A.	ES	1459.2
Landesbank Hessen-Thueringen Girozentrale	DE	187.5	Banco Bilbao Vizcaya Argentaria, S.A.	ES	816.4
NRW.BANK	DE	151.9	Criteria Caixa, S.A., Unipersonal	ES	387.5
Volkswagen Financial Services AG	DE	132.0	BFA, Tenedora de Acciones, S.A.U.	ES	232.7
DekaBank Deutsche Girozentrale	DE	117.6	Banco de Sabadell	ES	227.1
HSH Nordbank AG	DE	105.6	Banco Popular Espanol S.A.	ES	172.7
Landwirtschaftliche Rentenbank	DE	101.6	Unicaja Banco S.A.	ES	65.7
Erwerbsgesellschaft der S-Finanzgruppe mbH & Co KG	DE	81.9	Ibercaja Banco, S.A.	ES	64.1
Deutsche Pfandbriefbank AG	DE	72.7	Bankinter	ES	63.9
Aareal Bank AG	DE	56.6	Kutxabank, S.A.	ES	63.6
HASPA Finanzholding	DE	49.4	ABANCA Corporacion Bancaria, S.A.	ES	51.5
Muenchener Hypothekenbank eG	DE	41.5	Liberbank S.A.	ES	45.9
State Street Bank International GmbH	DE	40.9	Banco Mare Nostrum S.A.	ES	44.4
Deutsche Apotheker- und Aerztebank eG	DE	39.7	Banco de Credito Social Cooperativo, S.A.	ES	10.3
SEB AG	DE	24.4			
National Bank of Greece S.A.	GR	121.0	Total assets		22804.9
Piraeus Bank S.A.	GR	95.7			
Eurobank Ergasias S.A.	GR	80.1			
Alpha Bank AE	GR	75.4			

Notes: 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; and ES = Spain. Assets for 2015 shown because that is the year when the number of banks (109) is greatest in the unbalanced (2007-2016) sample.

and deposits-to-assets—enables us to see the distribution of SSM assets by broad business models (Fig. 2). 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 of less than 8%, 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.

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 NPL ratio), which is coming down gradually, but progress remains uneven (Fig. 2). The average NPL ratio remained elevated in 2016, albeit concentrated in some banks, as reflected in the large standard deviation (Table 2). Overhead (non-

Table 2
Descriptive statistics of main variables.

		2007-2016				2016		
Variable	Description	Observations	Median	Mean	SD	Median	Mean	SD
ROA	Return on (average) assets	1047	0.42	0.33	1.60	0.47	0.34	1.20
ROE	Return on (average) equity	1047	8.19	2.08	49.73	8.20	4.03	15.98
Size	log (assets)	1081	11.29	11.35	1.62	11.13	11.21	1.44
Equity-to-assets	Equity-to-assets ratio	1081	5.93	6.95	7.16	7.08	7.80	3.83
GDP growth	Real GDP growth	967	1.19	0.79	3.34	1.86	2.08	1.17
Policy rate	ECB policy rate proxy: 3-month zero coupon yield on AAA euro area securities	1081	0.41	0.94	1.50	−0.62	−0.62	0.00
NPL ratio	Nonperforming loans-to-gross loans ratio	898	4.3	7.75	9.61	4.88	10.63	13.57
Cost-to-income	Overhead cost-to-operating income ratio	1080	59.9	35.54	743.83	62.65	66.11	23.08
Loans-to-assets	(Total) loans-to-(total) assets ratio	1065	62.73	58.15	22.11	64.70	59.07	20.63
Deposits-to-assets	(Total) customer deposits-to-(Total) assets ratio	1045	44.76	44.69	22.11	53.06	52.12	22.27
Noninterest income-to-revenue	Noninterest revenues-to-total operating income ratio	1077	33.11	35.57	160.33	36.89	35.29	34.32
Concentration	Share of five largest bank assets relative in total bank assets (country-specific)	1081	47.4	52.03	19.76	45.95	54.44	18.95

Sources: Fitch Connect, European Central Bank, and authors' calculations.
Note: Negative income in some years for some banks reduces the average cost-to-income ratio over 2007-2016. When these observations are removed, the average increases to 62.5%, which is closer to the median.

Table 3
Stylized facts: Key bank-specific determinants ROE quintile buckets (in%).

	<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-to-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-to-income ratio	81.2	70.2	61.7	52.2
Loans-to-assets	67.9	58.7	51.1	66.0
Deposits-to-assets	51.5	48.4	47.2	59.0

Sources: FitchConnect, ECB, and IMF staff calculations.
Notes: Data in% unless stated otherwise. 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.

interest) costs, as a share of operating income, are higher in 2016 than the sample average, likely reflecting the inertia of expenses related to large branch networks and the servicing of nonperforming loans for traditional banks, and fees and fines for others. Other key bank-specific characteristics vary notably across banks as well.

Average GDP growth, which included both the crisis and the recovery, is below the current estimates of potential growth. Over the 2007–2016 sample that is considered in the analysis, average real GDP growth was 0.8%, with wide cross-country differences due to both the global financial crisis and the European debt crisis (the standard deviation of growth was 3.3% as shown in Table 2). In 2016, the growth rate rose to 1.2% and its standard deviation declined. This observation is in line with the synchronized nature of the recovery of the euro area countries that year, with all countries growing, and the variation in growth among countries at its lowest since the advent of the euro. Nevertheless, and at the time of writing, conjunctural projections have deteriorated again.

Slicing through the ROE distribution reveals monotonic trends associated with the NPL and cost-to-income ratios. Table 3 shows the main bank-specific characteristics across four ROE levels in 2016: below the 25^{th} percentile (<Q1), between the 25^{th} and 50^{th} percentile (Q1–Q2), between the 50^{th} and 75^{th} (Q2–Q3), and above the 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%, 20 percentage points worse than that of the next quartile, and the ROE in the top quartile is only about 5%age points higher than in the second highest. Banks in the left end of the distribution have an ROA of –1%, an NPL ratio of 22%, and a cost-to-income ratio of 81% on average. These banks 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.

4. Econometric analysis

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

4.1. Benchmark OLS regression analysis

The baseline results show that real GDP growth and the NPL ratio are the most reliable determinants of bank profitability. Specifically, Table 4 shows the baseline ROA specification under the first column, as well as key ROA components as dependent variables to 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. Accordingly, a one standard deviation increase in growth—observed to be 3.3% over the sample (Table 2)—would translate into 91 basis points of increase in the ROA.

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. Of note, a one standard deviation reduction in NPLs (which corresponds to 9.6% over the sample), is associated with a 48 basis point increase in the ROA.

On average, the link between ROA and cost-to-income, concentration, and business model indicators are estimated less precisely. In the case of business models in particular, these mixed results could reflect the coarse nature of the available proxies. Although differences in sample, specifications, and econometric methodology render comparisons difficult, these findings overall are broadly similar to those of the studies discussed above.

The components of ROA were then used as dependent variables to explore the channels at play (Table 4). Specifically, we consider the roles of net interest income, non-interest income, and loan loss provisions as dependent variables (which are all scaled by assets

Table 4
Baseline profitability regressions: Return on assets and components and robustness.

Variables	(1) ROA	(2) ROA	(3) Net Interest Income/ Assets	(4) Net Interest Income/ Assets	(5) Noninterest income/ Assets	(6) Noninterest income/ Assets	(7) Loan loss provisions/ Assets	(8) Loan loss provisions/ Assets	(9) Cost/ Assets	(10) Cost/ Assets	(11) Pre-provision ROA	(12) Pre-provision ROA	(13) ROE	(14) ROE
Size (log assets) (-1)	−0.532**	−0.437	−0.106	−0.0617	−0.265***	−0.271***	0.210	0.149	0.0007	4.55e-05	−0.457***	−0.405**	−5.923	−7.569
	(0.2590)	(0.273)	(0.0969)	(0.0890)	(0.0667)	(0.0670)	(0.2520)	(0.264)	(0.0711)	(0.0693)	(0.1480)	(0.159)	(12.44)	(11.40)
Equity-to-assets (-1)	0.0314	0.0108	0.0446***	0.0348***	−0.00335	−0.00167	−0.0138	−0.00202	0.00969	0.00981*	0.0126	0.00313	−0.0338	0.327
	(0.0454)	(0.0354)	(0.0079)	(0.00658)	(0.0069)	(0.00547)	(0.0384)	(0.0317)	(0.0069)	(0.00504)	(0.0210)	(0.0162)	(1.392)	(1.071)
GDP growth	0.272***	0.274***	0.00542	0.00663	0.0111*	0.0108*	−0.199***	−0.200***	−0.00565	−0.00566	0.0730	0.0741	4.329**	4.286**
	(0.0681)	(0.0678)	(0.0077)	(0.00744)	(0.0062)	(0.00608)	(0.0348)	(0.0348)	(0.0054)	(0.00537)	(0.0474)	(0.0469)	(1.681)	(1.679)
NPL ratio (-1)	−0.0457**	−0.0459**	−0.00407	−0.00422	−0.000394	−0.000288	0.0283*	0.0285*	0.0092***	0.00915***	−0.0168*	−0.0168*	−0.416	−0.412
	(0.0217)	(0.0220)	(0.0042)	(0.00425)	(0.0044)	(0.00440)	(0.0167)	(0.0169)	(0.0031)	(0.00314)	(0.0086)	(0.00874)	(0.422)	(0.420)
Cost-to-income (-1)	−0.00304		−0.00139***		0.000141		0.00173		0.0000		−0.00150		0.0523	
	(0.0022)		(0.0005)		(0.0004)		(0.0017)		(0.0004)		(0.0009)		(0.119)	
Loans-to-assets (-1)	−0.0134	−0.00969	0.00609**	0.00790***	−0.000838	−0.00123	0.0194	0.0172	0.00391**	0.00389**	0.00490	0.00665	0.217	0.151
	(0.0141)	(0.0130)	(0.0026)	(0.00231)	(0.0022)	(0.00212)	(0.0124)	(0.0117)	(0.0017)	(0.00168)	(0.0049)	(0.00439)	(0.527)	(0.417)
Deposits-to-assets (-1)	0.00791	0.0116	0.00501*	0.00675***	0.00229	0.00204	−0.0160**	−0.0181**	0.0061***	0.00606***	−0.00860	−0.00679	0.137	0.0726
	(0.0106)	(0.0104)	(0.0026)	(0.00252)	(0.0026)	(0.00241)	(0.0080)	(0.00750)	(0.0016)	(0.00153)	(0.0060)	(0.00623)	(0.279)	(0.247)
Noninterest income-to-revenue (-1)	−0.00206		−0.00108**		0.000348		0.0013		0.0000		−0.000885		0.0379	
	(0.0016)		(0.0004)		(0.0003)		(0.0012)		(0.0003)		(0.0007)		(0.0866)	
Concentration (-1)	−0.00937	−0.0126	−0.00421	−0.00567	0.00116	0.00125	0.0218*	0.0237*	0.0003	−0.000283	0.0132	0.0116	0.425	0.481
	(0.0213)	(0.0211)	(0.0043)	(0.00427)	(0.0042)	(0.00406)	(0.0126)	(0.0121)	(0.0030)	(0.00284)	(0.0139)	(0.0142)	(0.526)	(0.553)
Observations	794	794	794	794	794	794	791	791	795	795	791	791	794	794
R-squared	0.482	0.479	0.904	0.902	0.662	0.661	0.480	0.479	0.855	0.855	0.534	0.532	0.220	0.219

Notes: Bank and year fixed effects not shown. Standard errors, clustered by country*year, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

to facilitate comparability to ROA).[16] Higher growth results in a rise in noninterest revenue streams (columns 5-6) and a decline in loan-loss provisioning (columns 7-8), results that are consistent with Altavilla, Boucinha, and Peydro (2018). The negative correlation between loan loss provisions and growth is also in line with Huizinga and Laeven (2019). This suggests that the procyclicality of ROA is driven primarily by a greater demand for financial services (resulting in higher fees and commissions), trading income, and enhanced asset quality during an upswing. Lower NPL ratios would reduce provisioning costs and, hence, increase ROA. Note also that 60% of the effect of lagged NPLs on ROA stem from the provisioning needs (based on columns 1-2 and 7-8).

Table 4 also includes regressions where the costs-to-assets ratio and pre-provision ROA are dependent variables (shown in columns 9-10 and 11-12, respectively). These supplementary regressions provide evidence suggesting that elevated NPL stocks are associated with costs other than those directly related to provisioning (such as operational and legal expenses). Indeed, a higher NPL ratio is associated with a lower pre-provision ROA. Table 4 also includes a few complementary regressions to highlight robustness: the cost-to-income and noninterest income-to-revenue variables are omitted for each ROA component (and for ROE, which is added to the table for completeness).

4.2. Robustness analysis

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 sovereign securities). The baseline specification is also re-estimated using a balanced sample as well as with the general method of moments (GMM).

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, loan loss provisions, and the likely reduced availability of funds to lend. Since the GDP growth term is included, and attention focuses on medium-term effects, the NPL flow term is not included in further analysis.

A steeper yield curve or higher short-term interest rates do not appear to help profitability of these banks on average, which is in line with the findings of Altavilla, Boucinha, and Peydro (2018). 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-

[16] Recall that ROA is calculated by dividing net income (before extraordinary items and taxes) by the (average) value of total assets. In turn, net income (before extraordinary items and taxes) can be defined as net interest income (NII) plus net non-interest income minus loan loss provisions minus operating costs (where NII = Interest income − Interest expense and Net non-interest income = Trading income + Fees and commissions + Other operating income). Operating costs include branch and personnel costs.

Table 5
Robustness analysis: Return on assets.

	(1)	(2)	(3)	(4)	(5)	(6)	(Balanced)	(GMM)
Size (log assets) (-1)	−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)
Equity-to-assets (-1)	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)
GDP growth	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)
NPL ratio (-1)	−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)
Cost-to-income (-1)	−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)
Loans-to-assets (-1)	−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)
Deposits-to-assets (-1)	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)
Noninterest income-to-revenue (-1)	−0.00206	−0.00112	−0.000100	−0.00129	0.000104	−0.00227	−0.00207	−0.00930***
	(0.00161)	(0.00166)	(0.00240)	(0.00184)	(0.00210)	(0.00164)	(0.00276)	(0.00321)
Concentration (-1)	−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)
NPL ratio, change		−0.154**						
		(0.0607)						
Loan growth			−1.78e-06					
			(1.90e-06)					
FCI				−0.390**				
				(0.174)				
Yield curve slope					−0.0140			
					(0.0265)			
Policy rate						0.0392		
						(0.0474)		
ROA (-1)								−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	

Bank and year FE; standard errors clustered by country*year. Column (6) does not have year FE. For the GMM column, no explanatory variable, except for profitability, is lagged.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

sale portfolio, for instance). Since the crisis, the maturities 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.[17] Furthermore, higher interest rates could push highly indebted bank borrowers to default on their loan payments, which 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 in this sample.[18] For related findings, see Alessandri and Nelson (2015).

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.

Including a lagged dependent variable or using a balanced sample would highlight the robustness of the main findings. Following Kok, More, Pancaro (2015), 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.

Using ROE yields broadly similar findings. The regressions discussed above were estimated using ROE as the main profitability indicator, and again indicate that 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 motivate the use of quantile regression analysis.

A final robustness check considered risk-adjusted profitability metrics. Following Demirgüç-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 con-

[17] Likewise, Tan (2019) suggests that net interest margins are overall unaffected when policy rates are negative because the volume effect (of greater lending) is large enough to offset the adverse impact on bank profitability (but cautions that the positive effects on lending dissipate as negative rates persist). To further explore the relationship between bank profitability and the slope of the yield curve, we considered two additional robustness exercises. First, we used net interest margins (NIMs) as a dependent variable and then re-estimated the robustness specification which includes the slope of the yield curve. Second, we differentiated bank business models at the country level. Specifically, based on data availability, we considered the share of mortgage loans that price within one year. We then interacted this share variable with the slope of the yield curve. The coefficients on the interaction term and the slope of the yield curve were mixed and statistically insignificant.

[18] When assessing the impact of low interest rates on banks’ NIMs, it is important to distinguish between banks granting loans at floating versus fixed rates. The level of short-term interest rates is more important for NIMs of banks with predominantly floating-rate loans, while the slope of the yield curve plays a relatively greater role for banks with a larger share of fixed-rate loans. Furthermore, interest rate effects will differ across business models; the sample excludes smaller, purely retail-oriented banks.

Table 6
Return on equity regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(Balanced)	(GMM)
Size (log assets) (-1)	−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)
Equity-to-assets (-1)	−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)
GDP growth	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)
NPL ratio (-1)	−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)
Cost-to-income (-1)	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)
Loans-to-assets (-1)	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)
Deposits-to-assets (-1)	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)
Noninterest income-to-revenue (-1)	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)
Concentration (-1)	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)
NPL ratio, change		−3.318***						
		(1.082)						
Loan growth			−8.08e-06					
			(4.33e-05)					
FCI				−9.982				
				(8.820)				
Yield curve slope					0.0759			
					(1.478)			
Policy rate						2.366		
						(1.511)		
ROE (lag)								−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	

Bank and year FE; standard errors clustered by country*year. Column (6) does not have year FE. For the GMM column, no explanatory variable, except for profitability, is lagged.
*** p<0.01, ** p<0.05, * p<0.1.

structed 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 in the time dimension. 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.

4.3. Quantile regression analysis

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 Tables 8 and 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 25^{th} to the 75^{th} quantiles in both sets of regressions. For example, in the ROA regressions, the growth coefficient is 0.2 and 0.09 in the 25^{th} and 75^{th} quantile regressions, respectively. A similar pattern holds in the case of the NPL ratio. Of note, although only GDP growth and the NPL ratio are statistically significant for the 25^{th} quantile ROA regression, all determinants are statistically significant for the 75^{th} quantile regression. Taken together, 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.

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. Changes to business models hold promise as well. Evidence points to a positive correlation between ROA and a greater deposit-to-asset ratio.[19]

5. Conditional Profitability Distributions

This section discusses the conditional profitability distributions and how shocks to the underlying bank-specific determinants alter the shape of these distributions.

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. Recognizing that the 2007-2016 sample period includes several cri-

[19] Recall that the quantile regressions include both bank and time fixed effects terms. In addition, these regressions were estimated using robust standard errors, bootstrapped standard errors, and clustered standard errors (at the country level, following Parente and Santos Silva 2016). The main findings are robust to these complementary error structure assumptions (for example, growth and NPLs remain statistically robust across quantiles). We also implemented the new method for estimating quantile regressions using panel data from Machado and Santos Silva (2019). Although these tables were suppressed in the interest of brevity, they are available upon request.

Table 7
Robustness analysis: Risk-adjusted profitability measures.

	ROA/SD		ROE/SD		Z-Score	
VARIABLES	(1) Full	(2) Balanced	(3) Full	(4) Balanced	(5) Full	(6) Balanced
Size (log assets) (-1)	−0.0107	−0.663	0.0695	−1.176*	−2.130	−6.517
	(0.506)	(0.617)	(0.703)	(0.629)	(5.782)	(6.798)
GDP growth	0.0806	−0.00968	0.0734	1.209	−0.418	−5.729
	(0.195)	(0.974)	(0.209)	(1.310)	(2.297)	(7.524)
NPL ratio (-1)	−0.331***	−0.380***	−0.355***	−0.375***	−2.928***	−3.774***
	(0.0578)	(0.0795)	(0.0673)	(0.0733)	(0.568)	(0.822)
Cost-to-income (-1)	−0.000401	−0.0919*	0.00181	−0.0766	0.0369	−0.461
	(0.00299)	(0.0538)	(0.00392)	(0.0519)	(0.0458)	(0.531)
Loans-to-assets (-1)	0.00520	−0.0968*	−0.00186	−0.0561	−0.457	−0.877
	(0.0424)	(0.0505)	(0.0402)	(0.0409)	(0.488)	(0.617)
Deposits-to-assets (-1)	0.0928**	0.116*	0.101***	0.0613	0.368	0.924
	(0.0358)	(0.0624)	(0.0373)	(0.0439)	(0.567)	(0.769)
Noninterest income-to-revenue (-1)	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

Full and balanced denote full and balanced samples, respectively.
Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 8
Quantile regressions: Return on assets.

	OLS	Quantile regressions		
VARIABLES	(1)	(2) 25th	(3) 50th	(4) 75th
Size (log assets) (-1)	−0.532**	−0.221	−0.111	−0.252**
	(0.259)	(0.316)	(0.216)	(0.117)
Equity-to-assets (-1)	0.0314	0.0229	0.0504***	0.0439***
	(0.0454)	(0.0279)	(0.0191)	(0.0103)
GDP growth	0.272***	0.201***	0.135***	0.0864***
	(0.0681)	(0.0258)	(0.0176)	(0.00955)
NPL ratio (-1)	−0.0457**	−0.0752***	−0.0455***	−0.0103**
	(0.0217)	(0.0113)	(0.00772)	(0.00418)
Cost-to-income (-1)	−0.00304	−0.00202	−0.00312**	−0.00192***
	(0.00219)	(0.00192)	(0.00131)	(0.000710)
Loans-to-assets (-1)	−0.0134	−0.0118	−0.00949	−0.00639*
	(0.0141)	(0.00953)	(0.00650)	(0.00352)
Deposits-to-assets (-1)	0.00791	0.00837	0.00531	0.00888**
	(0.0106)	(0.00985)	(0.00672)	(0.00364)
Noninterest income-to-revenue (-1)	−0.00206	−0.00122	−0.00230**	−0.00145***
	(0.00161)	(0.00150)	(0.00102)	(0.000553)
Concentration (-1)	−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 not shown.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

sis episodes, the specifications include time fixed effects terms which help account for such turbulent periods. The distribution has a mean of 5%, a mode of 9%, and a sizeable standard deviation of 20%.[20] The shape of the conditional distribution is particularly noteworthy as it has a long left tail of chronically low-profitability banks (Fig. 3).[21]

The shape of the conditional ROE distributions changes 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 and considers how changes in these determinants influence the entire ROE distribution. For instance, higher growth (a positive one standard deviation increase relative to the sample average) pulls the distribution to the right. Notice that along with a higher mean, the variance seems to have decreased, and the shocked distribution is less leptokurtic. In particular, notice the thinning of the left tail in contrast to the increase in mass around what appears to be a ROE level of about 12%. Interestingly, a lower NPL ratio (a negative one standard deviation decreases relative to

[20] In contrast to the data used in the earlier econometric analysis—and purely to facilitate smoother distributions that are more visually appealing—the ROE data used to estimate the decile regressions were "winsorized" by 7.5% on both sides (Appendix Table 1). The results are robust to winsorization at the 5, 2.5, and 1% levels (and available upon request).

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

Table 9
Quantile regressions: Return on equity.

	OLS	Quantile regressions		
	(1)	(2)	(3)	(4)
VARIABLES		25th	50th	75th
Size (log assets) (-1)	−5.923	−7.343	−5.167	−5.088***
	(12.44)	(7.418)	(3.486)	(1.733)
Equity-to-assets (-1)	−0.0338	0.0709	−0.152	−0.606***
	(1.392)	(0.655)	(0.308)	(0.153)
GDP growth	4.329**	3.372***	1.864***	1.045***
	(1.681)	(0.606)	(0.285)	(0.142)
NPL ratio (-1)	−0.416	−0.863***	−0.438***	−0.151**
	(0.422)	(0.265)	(0.125)	(0.0620)
Cost-to-income (-1)	0.0523	−0.0257	−0.00930	0.0158
	(0.119)	(0.0451)	(0.0212)	(0.0105)
Loans-to-assets (-1)	0.217	−0.227	−0.125	−0.113**
	(0.527)	(0.224)	(0.105)	(0.0522)
Deposits-to-assets (-1)	0.137	0.0660	0.0256	0.0960*
	(0.279)	(0.231)	(0.109)	(0.0540)
Noninterest income-to-revenue (-1)	0.0379	−0.0290	−0.00749	0.00964
	(0.0866)	(0.0351)	(0.0165)	(0.00820)
Concentration (-1)	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 not shown.
Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10
Summary: Conditional profitability (ROE) distributions. (percent).

ROE Threshold:	<8	>8
Baseline	82.5	17.5
Higher Growth	61.4	38.6
Lower NPLs	71.9	28.1
Higher growth and Lower NPLs	49.1	50.9
Descriptive statistics	Mean	Standard deviation
Growth	0.8	3.3
NPL	7.4	8.9

Source: Authors' calculations.
Notes: Return on equity (ROE) is used to measure profitability. Results are shown for ROE over (under) 8%. These probabilities are calculated using baseline and shocked distributions, where 1 standard deviation shocks are used. Selected sample descriptive statistics are included.

the sample average) results in a broadly similar shift to the right as well. However, notice that 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.

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% threshold are now computed. Table 10, which comprises two columns (above and below 8% ROE, respectively), shows these probabilities. The first row depicts these probabilities under the baseline distribution for 2016. The next three rows tabulate the probabilities in response to one standard deviation shocks: higher growth, a lower NPL ratio, or their combination. Note that these are large shocks: over our 2007–2017 sample, the standard deviations of growth and the NPL ratio were 3.3% and 8.9%, respectively.

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 probability of a "representative" bank in the sample having ROE less than 8% is 83%; i.e., 83% of the distribution is below 8%.[22]

An increase in the growth of one standard deviation reduces the likelihood of ROE being below 8% to 61%, and correspondingly raises the probability of a bank with ROE greater than 8% by 21%age points (to 39%). Hence, while higher growth would naturally raise banks' profitability prospects, the shock under consideration is large. Moreover, notwithstanding the finding that average bank profitability increases, even under this higher growth scenario, the odds of a bank's ROE being below 8% remain elevated.

The quantitative effects of a one standard deviation decrease in the NPL ratio results in a broadly similar change to the contours of the profitability distribution (Fig. 3). The likelihood of ROE below 8% declines to 72% under this scenario.

The implications of a joint shock, whereby growth increases by one standard deviation and the NPL ratio decreases by the same magnitude, are now investigated. Three distributions are shown: the baseline, the distribution whereon growth is shocked, and the distribution where both growth and NPLs are shocked. The distribution reflecting the joint shocks indicates that the probability of a bank with ROE of less than 8% now declines to 49%—a difference relative to the baseline of about 33percentage points. Importantly, the joint materialization of these two shocks reduces the probability of ROE falling below 8% by more than if these shocks were considered individually (a reflection of underlying nonlinear interactions).[23] This scenario could be interpreted as demonstrating the

[22] Recall that these distributions are based on all banks over 2007–2016, which includes episodes of turbulent market conditions (another reason why time fixed effect terms were included). Moreover, notwithstanding the pooled nature of the exercise, the parameter estimation does take into account the degree of bank-specific heterogeneity over the cross-section (and over time) given the inclusion of bank and time fixed effects terms. Note also that the winsorization of the ROE data reduces the impact of extremely negative earning outturns on the results.

[23] In line with the results in Table 9, the regressions in Appendix Table 1 indicate that profitability in the lower ends of the distribution is more sensitive to changes in growth and the NPL ratio.

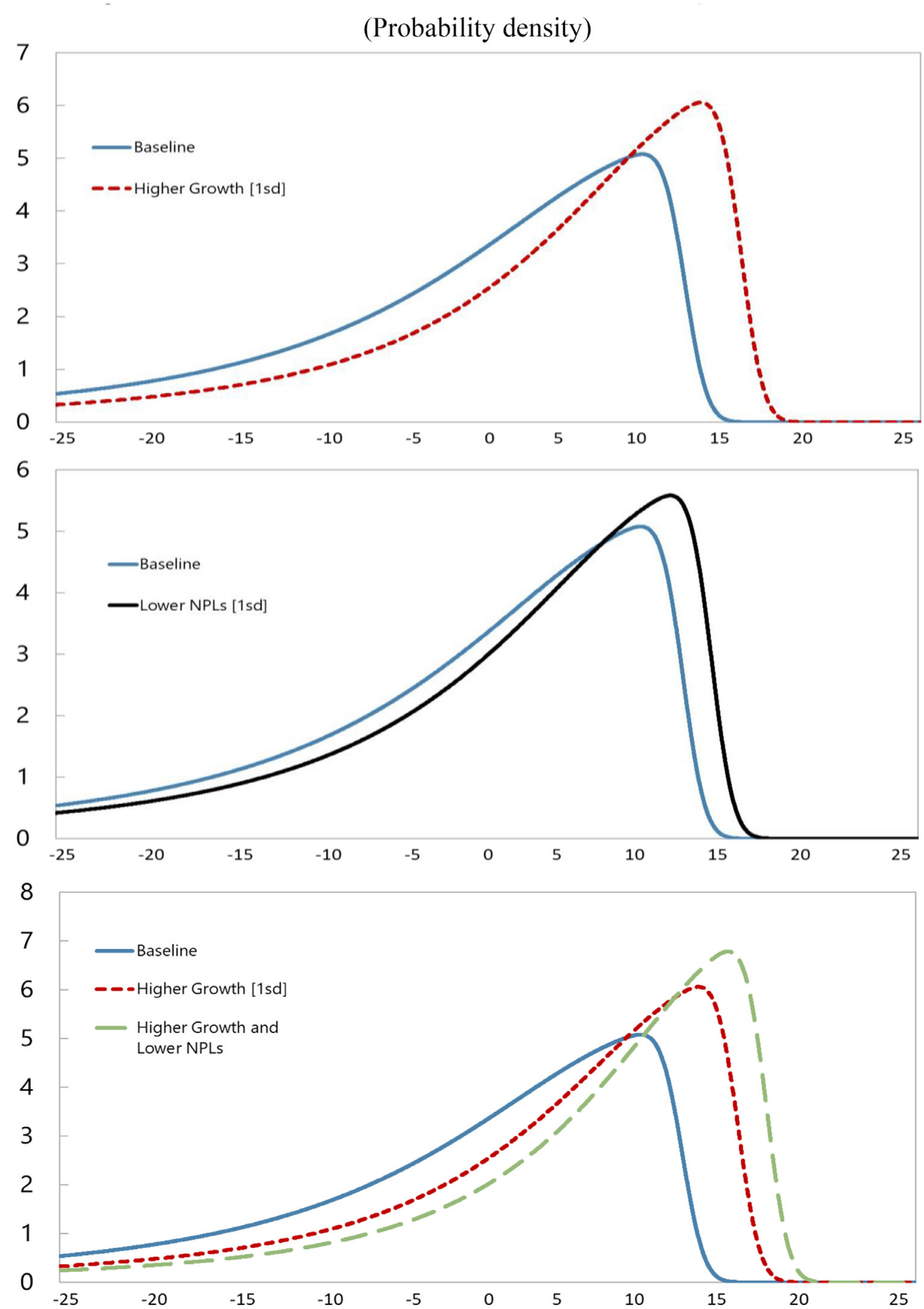

Fig. 3. Illustrative Conditional Profitability (ROE) Distributions. *Source:* Authors' estimates. Note: The figure shows illustrative baseline and "shocked" conditional bank ROE probability distributions for a "representative" bank. The distributions are conditional on determinants based on unbalanced quantile regressions for 109 SSM banks over 2007–2016 (which include bank and time fixed effect terms). y-axis has been scaled by 100.

benefits of a determined reduction of NPLs amid an economic upswing.[24]

[24] Despite using a different approach, sample period, and smaller set of banks, Andersson and others (2018) reach broadly similar conclusions. Specifically, they argue that even under a scenario that is much more favorable than those considered in this paper (which imposes ROE improvements motivated by cost-efficiency gains, income diversification, and advancements in digitization), around 25% of the banks would still remain below the indicative ROE threshold of 8%.

6. Conclusions and policy implications

This paper attempts to shed light on the main determinants of the profitability of larger euro area banks. The paper proposes a probabilistic approach that places greater emphasis on bank heterogeneity by focusing on bank profitability distributions. To facilitate comparability with the existing literature, the paper first establishes the most reliable determinants of bank profitability across the largest euro area banks. Selected determinants are then shocked to assess how they differentially affect segments of the bank profitability distribution. Specifically, higher economic growth, or a lower NPL ratio, for example, may affect the center of the bank profitability distribution in a different manner relative to how they may influence the tails of the distribution. In this way, the approach in this paper goes beyond the standard comparative statics centered on averages in many studies, and can be particularly insightful.

The empirical analysis reveals that real GDP growth and the NPL ratio are the most reliable medium-term determinants of euro area bank profitability. A key insight of the paper is that although higher growth would raise profits on average, a significant share of banks in the weakest tail of the profitability distribution would most likely continue to struggle, even with a cyclical upswing. Therefore, some banks, in particular, should resolutely address their NPL stocks. In addition, evidence suggests that greater cost efficiency (through digitalization, for example) could enhance the profitability of many banks. Although the results on business models were more mixed across all banks, revamping business models could improve profitability for some banks, suggesting the need for custom-tailored approaches. In terms of future research, a global sample of banks could be used to assess how the main determinants of bank profitability—including the role of (short-term) interest rates, the slope of the yield curve, and their interplay with business models—varies across regions and financial systems.

CRediT authorship contribution statement

Selim Elekdag: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Sheheryar Malik:** Conceptualization, Methodology, Software, Validation, Writing - original draft. **Srobona Mitra:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing, Project administration.

Acknowledgements

The authors would like to thank Daniel Hardy, Hannah Hempell, Deniz Igan, Christopher Kok, James Morsink, Georges Pineau, Lev Ratnovski, Thierry Tressel, Laura Valderrama, and two anonymous referees and an associate editor for their insightful comments, and Rohit Goel, Elizabeth Mahoney, Jesse Siminitz for excellent research assistance and Kateryna Botsu for excellent editorial assistance.

Appendix

Table A1
Quantile regressions: Return on equity.

	Quantile regressions								
Variables	(1) 10th	(2) 20th	(3) 30th	(4) 40th	(5) 50th	(6) 60th	(7) 70th	(8) 80th	(9) 90th
Size (log assets) (-1)	−7.726	−8.229	−6.564	−4.563	−4.409	−3.668	−3.470	−4.166	−6.617
	(4.49)	(3.21)	(2.39)	(1.47)	(2.62)	(1.36)	(1.02)	(1.18)	(1.81)
Equity-to-assets (-1)	−0.146	0.122	0.190	−0.034	−0.186	−0.274	−0.453	−0.627	−1.061
	(0.40)	(0.28)	(0.21)	(0.13)	(0.23)	(0.12)	(0.09)	(0.10)	(0.16)
GDP growth	2.678	2.488	2.277	1.916	1.681	1.378	1.064	1.001	0.965
	(0.37)	(0.26)	(0.20)	(0.12)	(0.21)	(0.11)	(0.08)	(0.10)	(0.15)
NPL ratio (-1)	−0.542	−0.414	−0.451	−0.472	−0.464	−0.215	−0.160	−0.137	−0.180
	(0.16)	(0.12)	(0.09)	(0.05)	(0.09)	(0.05)	(0.04)	(0.04)	(0.06)
Cost-to-income (-1)	−0.006	−0.026	−0.031	−0.013	−0.009	0.002	0.013	0.020	0.035
	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Loans-to-assets (-1)	−0.131	−0.156	−0.102	−0.103	−0.130	−0.110	−0.123	−0.092	−0.101
	(0.14)	(0.10)	(0.07)	(0.04)	(0.08)	(0.04)	(0.03)	(0.04)	(0.05)
Deposits-to-assets (-1)	0.089	0.064	0.022	0.021	0.022	0.094	0.130	0.083	0.084
	(0.14)	(0.10)	(0.07)	(0.05)	(0.08)	(0.04)	(0.03)	(0.04)	(0.06)
Noninterest income-to-revenue (-1)	−0.021	−0.033	−0.021	−0.010	−0.008	0.000	0.007	0.012	0.024
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Concentration (-1)	−0.199	−0.292	−0.258	−0.196	−0.222	−0.179	−0.155	−0.140	−0.146
	(0.19)	(0.14)	(0.10)	(0.06)	(0.11)	(0.06)	(0.04)	(0.05)	(0.08)
Observations	798	798	798	798	798	798	798	798	798

Notes: Bank and year fixed effects not show. Standard errors in parentheses.

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