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DRIVERS OF PROFIT CONVERGENCE IN EURO AREA BANKS

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Abstract

Since there are persistent concerns about the viability of euro area banks, we analyse their profit recovery in the post-crisis period, applying the concepts of β and σ convergence as well as the Phillips and Sul clustering algorithm. The results are consistent with ROE convergence, but to different levels across bank groups. The clustering analysis reveals the existence of banks with solid performance, but also a group of persistent underperformers. We find that non-interest income and operational efficiency emerge as crucial discriminating factors to explain the banks' relative post-crisis ROE dynamics. Supervisors and bank managers are advised to monitor and reinforce bank business model viability.

Keywords: Euro Area banks; Bank profitability; β convergence; σ convergence; Club clustering analysis

1. Introduction

The Great Financial crisis (GFC) of 2008 and the subsequent European sovereign debt crisis caused substantial divergence in the profitability of euro area banks. While some banks were able to absorb the negative shocks, others were hit hard by non-performing loans and valuation losses on their assets. The question we address is whether or not the vulnerable banks have been able to recover and what the drivers of profit convergence are. This is of crucial importance for the euro area economy, since banks provide the bulk of the financing of corporations as well as households. Moreover, there is evidence that the weaknesses of the business model of vulnerable banks causes them to perform badly whenever a new crisis occurs (Fahlenbrach et al., 2012). In that respect, the persistent low market/book equity ratios exhibited by a substantial number of euro area banks is a signal that investors doubt the viability of the banks' business model. In the same vein, Altavilla et al. (2021) show that the average return on equity (ROE) of euro area banks has remained below their cost of equity (COE) for the entire post-GFC period. As a result, the Supervisory Board of the European Central Bank has voiced concerns about the long-term profit potential of the banks (Enria, 2023). To assess the banks' longer-term profit potential, we investigate the post-crisis convergence of bank profitability and the underlying drivers.

Several papers have researched convergence in European banking, but the focus is mostly on operational efficiency of banks (Casu & Girardone, 2010; Degl'Innocenti et al., 2017; Matousek et al., 2015). In terms of overall profitability, we expect convergence because euro area banks operate in an environment characterised by similar regulations (e.g. Basel III), supervision (by the ECB) and monetary policy conditions (Altavilla et al., 2018; Loipersberger, 2018). This may induce similar behaviour by the banks. Nevertheless, we also hypothesise that performance of some banks may diverge resulting from negative shocks combined with unfavourable initial conditions (e.g. legacy bad loans) or a deficient risk culture (Fahlenbrach et al., 2012). Lamers et al. (2022) report that euro area banks' ROE recovered in the period between the GFC and the covid pandemic, but do not address the underlying drivers. We extend this analysis by focusing on the building blocks of bank ROE, such as the net interest margin, income diversification, cost efficiency and asset quality. In terms of empirical design, we use the Phillips and Sul (PS) clustering approach, as in Matousek et al. (2015), but we apply it to the underlying drivers of bank profits.

2. Data and Methodology

2.1 Data

Since we focus on profit convergence following the GFC and sovereign crisis, the period under investigation is 2013-2021. The PS clustering algorithm requires banks to be present in the sample over the entire period. Therefore, we use a balanced sample of 80 euro area banks under ECB supervision. Overall bank profitability is captured by ROE[1], but we also analyse the underlying components, i.e. the net interest margin (NIM), non-interest income (NONINT/total income), cost efficiency (cost/income-ratio, C/I) and non-performing loans (NPL/Loans) (Davis et al., 2022; Mergaerts and Vander Vennet, 2016). The data is retrieved from S&P Capital IQ Pro, and Table 1 presents the summary statistics for the profit variables as well as other relevant bank characteristics.

Table 1: Summary statistics (winsorised data: 5%-95%)

	n	mean	median	min	max	sd
Size (=log(TA))	825	18.15	18.07	12.94	21.69	1.59
ROA	816	0.44	0.44	-1.63	1.65	0.68
ROE	816	6.04	7.28	-24.78	21.11	9
NIM	782	1.4	1.34	0.35	2.74	0.64
NONINT/TI	813	37.7	38.93	-0.5	74.27	18.23
C/I	813	62.31	61.57	40.34	87.29	12.87
NPL/Loans	792	6.1	3.06	0.43	30.22	7.83
CET1/RWA	793	16.42	14.94	6.63	29.43	5.17
RWA/TA	806	39.56	36.57	14.25	75.48	16.35
Loans/TA	812	58.98	60.84	23.38	82.47	15.86
Deposits/TA	703	67.61	73.03	30.63	88.34	17.16

[1] ROE is computed as net income before tax divided by total equity; we use before tax profit since tax regimes are different depending on the country in which a bank is headquartered.

2.2 Methodology

2.2.1 Beta and Sigma Convergence

To investigate convergence of bank performance, we use the concepts of β and σ convergence, introduced by Barro and Sala-I-Martin (1992). The initial purpose of these concepts was to investigate the presence of convergence between rich and poor countries in terms of GDP per capita. In the context of bank performance, β convergence would imply that banks with an initially lower performance realise a higher ROE growth rate compared to banks that already perform better. The σ convergence would then indicate a lower dispersion in bank performance across euro area banks. Similar to Lamers et al. (2022), we estimate the following equations:

$$\Delta PERF_{i,t} = \alpha_p + \beta\ PERF_{i,\ t-1} + \varepsilon_{i,t} \qquad (1)$$

$$\Delta W_{i,t} = \alpha_w + \sigma\ W_{i,t-1} + \mu_{i,t} \qquad (2)$$

The variable $PERF_{i,\ t}$ refers to the performance (ROE and the underlying components) of bank i at time t. The dependent variable in equation (1) is the difference of $PERF_i$ between time t and time t-1. To analyse σ convergence we need $W_{i,t} = PERF_{i,t} - \overline{PERF_t}$, with $\overline{PERF_t}$ the average of the profitability of all banks at time t. The dependent variable in equation (2) is the difference in $W_{i,t}$ between time t and time t-1.

The presence of β (σ) convergence is confirmed if the β- (σ-) coefficient is negative and significant. β convergence is a necessary but not a sufficient condition for σ convergence to occur (Weill, 2009).

2.2.2 Phillips and Sul Clustering Algorithm

To analyse groups of banks with different profit dynamics, we use the model introduced by Phillips and Sul (2007, 2009) because it dynamically establishes convergence clusters, the model eliminates the need for assumptions about stationarity, and offers the possibility of different transitional paths (Sichera & Pizzuto, 2019). This method is a non-linear time-varying factor model with both common and individual specific components (Phillips & Sul, 2007). According to Phillips and Sul (2007), if we find clusters of banks with varying profit dynamics, we can uncover the drivers of these different paths based on the characteristics of the banks.

In our econometric analysis, we use the package ConvergenceClubs in R, introduced by Sichera and Pizzuto (2019). The first step in this algorithm is to perform a log-t regression test for convergence on the whole sample. When the null hypothesis of convergence is rejected, there is either no convergence or there are clusters of convergence. To know which hypothesis prevails, the test should be performed again on subgroups. The formula of this log-t regression test is as follows:

$$\log\frac{H_1}{H_t} - 2\log L(t) = a + b\ \log t + u_t \qquad (3)$$

$$\text{with} \quad H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{i,t}-1)^2\ ;\ h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N}X_{it}} \qquad (4)$$

In this analysis $L(t) = \log(t)$, as this is preferred over the other possibilities[2] in terms of asymptotic power and is thus the recommended L(t)-function in practice (Phillips & Sul, 2007). The term $h_{i,t}$ maps the transition path of an entity i (in our case this entity is a bank) relative to the average level.

Based on these formulae a (robust conventional) test statistic for the coefficient b must be computed[3] . For the null hypothesis to hold, b must be greater than or equal to 0. If the hypothesis gets rejected, the next step consists in finding subgroups with convergence. One of the benefits of the PS algorithm is that it provides a method to identify those subgroups, based on the data. The clusters are determined based on a repetition of the log-t regression test (Phillips & Sul, 2007).

The step-by-step procedure proposed by Phillips and Sul is as follows: (1) Order the entities based on their last observation; (2) Form a core group; (3) Add entities to the core group if they meet the condition (t > c* (a chosen critical value[4])); (4) Apply the stopping rule. The stopping rule consists of taking all the entities that did not meet the t>c* criteria together and test whether they form a cluster. If they do form a cluster, there are a total of two clubs and the procedure can be stopped; if it gets rejected by the log-t test, the step-by-step procedure is repeated on this subsample. Finally, to avoid overidentifying clusters a merging algorithm has to be applied to test whether some subsamples can be merged without rejecting the convergence hypothesis.

3. Results

3.1 β and σ convergence

Table 2 reveals negative β and σ coefficients for the whole sample, indicating convergence in terms of ROE towards a long-term level of 6.9%. The question is whether this is a general convergence or whether there are subgroups of banks that converge to different ROE levels. Therefore, we rank the banks from high to low ROE in 2013 and perform the analysis on the highest and lowest quartile. As shown in Table 2, the coefficients of these subgroups also indicate the presence of convergence. However, their estimated long-term convergence levels differ considerably (12.1% for the high performers versus 1.9% for the group of banks with low initial ROE) from the one obtained for the entire sample (6.9%). This suggests the presence of clusters of convergence with different profit paths. In order to uncover the dynamics of profitability across groups, and especially the underlying drivers, we apply the PS clustering algorithm as it does not rely on predetermined groups but lets the data yield the relevant clusters.

[2] $L(t) = log(log(t))$ or $L(t) = log(log(log(t)))$

[3] All details about the exact calculation and further explanation can be found in Phillips and Sul (2007, 2009).

[4] The higher the critical value, the higher the conservativeness meaning that banks have a lower probability to be assigned to the same cluster. For a large timespan (T>50) Phillips and Sul (2009) suggest -1.65 as critical value, for a smaller time span a bigger critical value is justified, Phillips and Sul (2009) then suggest 0.

Table 2: β and σ convergence ROE (pooled OLS[5]; 2013-2021)

	Beta convergence			Sigma convergence		
	Dependent variable:			*Dependent variable:*		
	ΔROE_t			$\Delta W_{ROE,t}$		
	Whole sample	Banks with high initial ROE	Banks with low initial ROE	Whole sample	Banks with high initial ROE	Banks with low initial ROE
	(1)	(2)	(3)	(4)	(5)	(6)
ROE_{t-1}	-0.473***	-0.334***	-0.605***			
	(-0.033)	(-0.101)	(-0.054)			
$W_{ROE,t-1}$				-0.466***	-0.273***	-0.641***
				(-0.037)	(-0.076)	(-0.059)
Constant	3.242***	-0.334***	1.154	-0.016	1.111*	-0.138*
	(-0.292)	(-0.101)	(-0.746)	(-0.302)	(-0.623)	(-0.074)
LT conv. Level	6.854	12.147	1.907	/	/	/
Observations	717	179	179	717	179	179
R^2	0.28	0.186	0.353	0.274	0.152	0.364
Adjusted R^2	0.279	0.181	0.349	0.273	0.147	0.361
F Statistic	278.114*** (df = 1; 715)	40.414*** (df = 1; 177)	96.473*** (df = 1; 177)	269.232*** (df = 1; 715)	31.793*** (df = 1; 177)	101.456*** (df = 1; 177)

Note: *p<0.1; **p<0.05; ***p<0.01 s.e. clustered at bank level.

3.2 Phillips and Sul Clustering Algorithm

By applying the clustering algorithm on the banks' ROE with a low c* value (c*=7), two clusters of convergence are found. Figure 1a, shows their average transition paths, relative to the sample average[6]. However, the first group contains the majority of the banks (73 of the 80 banks), hence it is too coarse. To obtain a more granular clustering, we apply a sequential clustering using higher c*'s (see footnote 4). The underperformers are retrieved from the initial run (club2 Figure 1a), while the outperformers are obtained from the clustering shown in Figure 1b (club1).

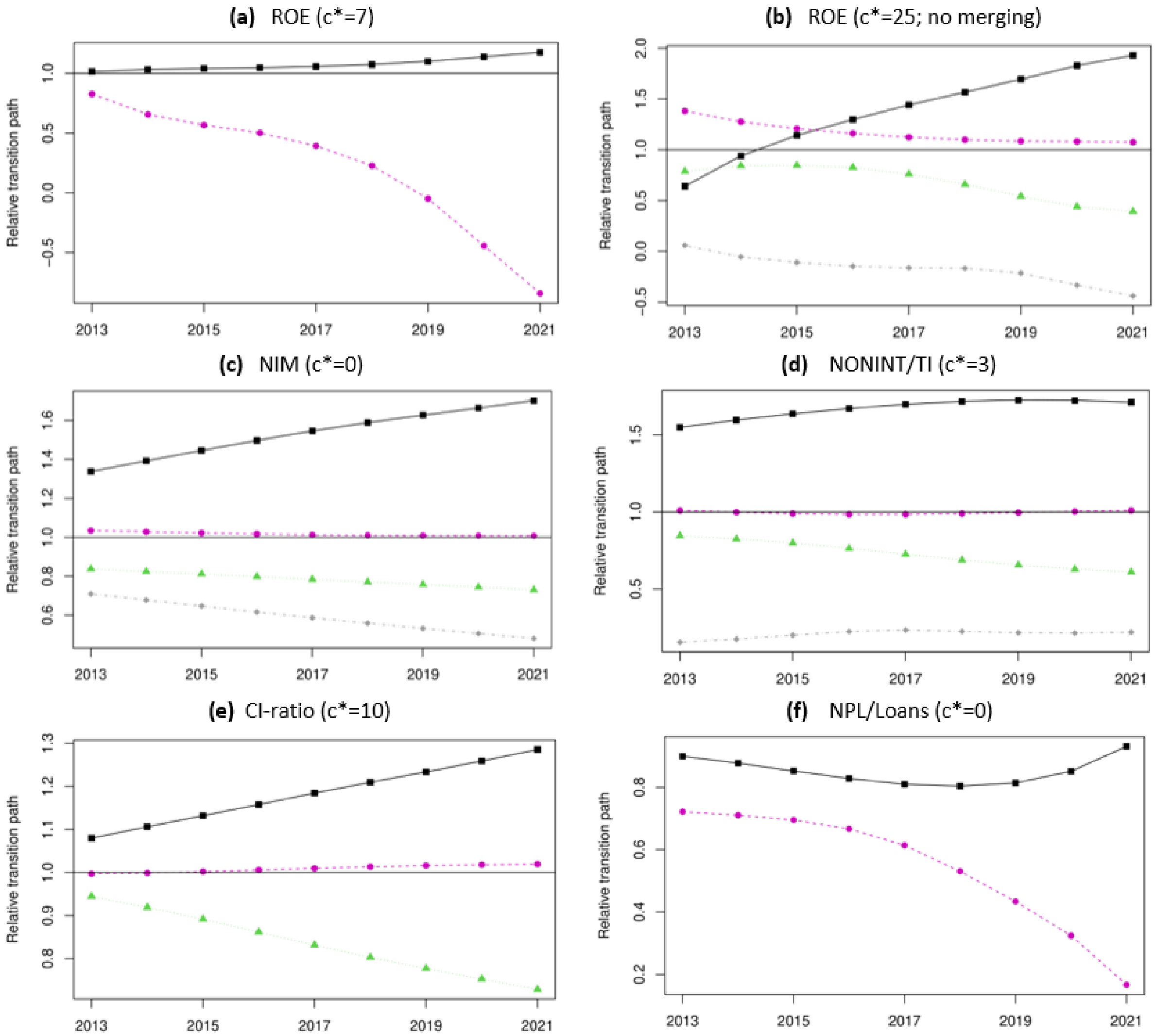
To uncover the behaviour of the underlying drivers of ROE, we apply the PS clustering to NIM, NONINT, C/I and NPL, yielding relative transition paths as depicted in Figure 1c/d/e/f. Clubs close to the

[5] Other estimations (FE, two-ways FE and RE) were also applied and they confirm the convergence result.

[6] The sample average is presented in the figures as a horizontal line at the unit level 1, with lines positioned above indicating superior performance compared to the average, while lines below indicate inferior performance.

sample average are deemed average performers, while those above (below) the neutral line are classified as outperformers (underperformers).

Figure 1: **Average transition path clubs based on mentioned clustering variable**



Note: club1: square, club2: dot, club3: triangle, club4: rhombus; **(f)** divergent units (5 banks) not in figure.

Having identified distinct performance groups through clustering, we analyse their associated bank characteristics to gain deeper insights into the dynamics behind these performance paths. On the diagonal of Table 3, we present the (statistically significant) differences between outperformers and underperformers for the variables of interest (ROE, NIM, NONINT, C/I and NPL) resulting from the club clustering analysis. Investigating the associated bank characteristics allows to identify the main drivers of bank profitability and how profits are related to the banks' risk profile.

Table 3: Overview average key summary statistics for each clustering result

Clustering variable			Average of bank characteristics								
			ROE	NIM	NONINT /TI	C/I-ratio	NPL /Loans	RWA /TA	CET1 /RWA	Loans /TA	Deposits /TA
(1)	ROE	Outperformers	8.73***	1.70	38.32***	58.92***	6.86***	42.48**	16.28	61.71	71.72**
		Underperformers	0.83***	1.63	31.01***	67.62***	13.76***	47.98**	16.97	60.24	64.60**
(2)	NIM	Outperformers	2.34***	2.12***	29.97***	60.00***	13.77***	54.61***	16.48	65.55***	75.74***
		Underperformers	6.85***	0.94***	48.78***	65.88***	3.71***	33.54***	15.75	50.12***	60.94***
(3)	NONINT /TI	Outperformers	8.65**	0.91***	63.02***	64.91***	3.20***	29.92***	16.33**	44.33***	57.19***
		Underperformers	4.93**	1.54***	19.74***	59.62***	7.59***	37.46***	18.00**	67.49***	67.57***
(4)	C/I-ratio	Outperformers	8.07***	1.49	30.06***	52.22***	4.74***	37.95	19.3***	65.54***	65.87
		Underperformers	1.42***	1.40	40.28***	74.09***	8.41***	39.70	15.11***	53.63***	65.71
(5)	NPL /Loans	Outperformers	6.51***	1.17***	39.95***	61.17	3.90***	32.68***	19.41***	60.26**	68.56***
		Underperformers	-4.94***	2.37***	21.82***	58.50	26.47***	57.70***	15.32***	65.68**	82.58***

Note: t-tests were performed to test whether there is a significant difference between the outperformers and underperformers. *, ** and *** indicate significance at 10%, 5% and 1% respectively.

The first row of Table 3 demonstrates that the clustering algorithm effectively distinguishes the good from the bad performers (ROE of 8.7% versus 0.8%)[7]. From the ROE row we also observe that the NIM is not a discriminating contributor, with similar margins for out- and underperformers. This can be attributed to the compressed bank NIMs during the low-interest-rate period caused by the unconventional monetary policy actions by the ECB (Claessens et al., 2018; Present et al., 2023). The first row suggests that the main contributors to a higher ROE are NONINT, C/I and NPL. Hence, revenue diversification, operational efficiency and asset quality appear as the dominant drivers of ROE. Since these variables reflect business model choices, competent bank managers should be able to increase the structural profitability of their banks.

These findings are confirmed when combining the ROE column and the values of the underlying drivers in rows 2-5. The NIM outperformers achieve a NIM of 2.12% versus 0.94% for the underperformers, but this is not translated in a superior ROE. In contrast, a higher NONINT (63% for the diversified banks versus 19.7% for the retail banks), a lower C/I (52.2% for the most efficient banks versus 74.1% for the underperformers) and lower NPL (3.9% for the banks with good loan quality versus 26.5% for those with the highest proportion of bad loans) is reflected in a significantly higher ROE. We conclude that, under the period of investigation, NIM, which is influenced by financial markets rather than bank management, was not a driver of ROE outperformance, whereas diversification, cost efficiency and NPLs are, and these are key performance indicators for bank managers.

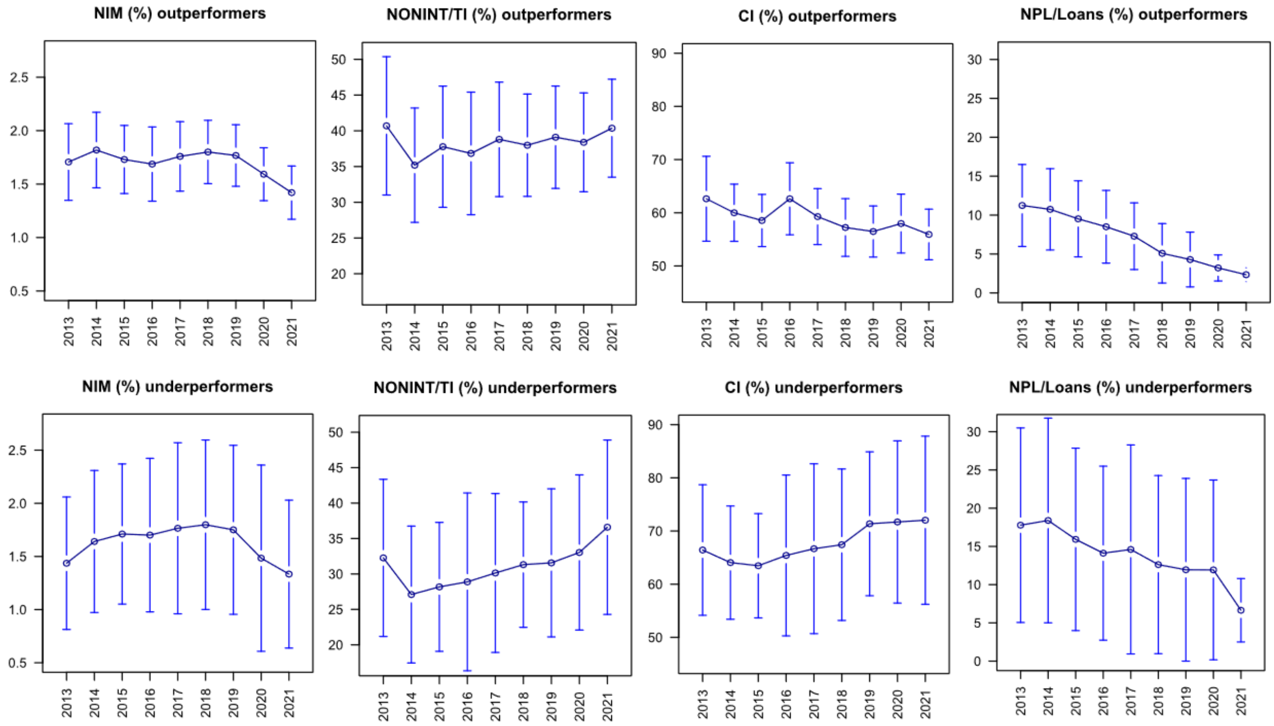
Finally, a higher ROE is not associated with more risk taking since CET1/RWA is not different for high and low-ROE banks, whereas RWA/TA is even lower for ROE outperformers. The balance sheet indicators loans/TA and deposits/TA exhibit the expected behaviour, e.g. high-NONINT diversified banks have significantly lower loans/TA and deposits/TA.

Besides averages it is important to look at temporal trends as well. Figure 2 shows declining NPLs and increasing non-interest income for underperforming banks, but a deteriorating cost-to-income ratio.

[7] The list of underperforming and outperforming banks in terms of ROE can be found in the Appendix. Both clusters contain banks headquartered in various countries, hence the clustering is not driven by the core periphery dichotomy.

Enhancing operational efficiency is thus imperative for their performance enhancement and long-term stability.

Figure 2: Evolution of bank characteristics for bank groups based on ROE clustering results



4. Conclusion

Our analysis reveals convergence of post-crisis performance of euro area banks, but we identify different clusters of ROE convergence, including a group of persistent underperformers. The clustering analysis of the underlying profit drivers uncovers that diversification of revenues on the income side and better cost efficiency and NPL management on the expenditure side are key to restore bank profitability. Bank supervisors, i.e. the ECB for euro area banks, should scrutinize the business model sustainability of the banks. If the bank cannot upgrade their performance through managerial actions, mergers and acquisitions, or even resolution in some cases, may be warranted to restructure the weak banks.

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