North American Journal of Economics and Finance 62 (2022) 101714

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

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

Commonality, macroeconomic factors and banking profitability

Orlando Joaqui-Barandica [a,*,1], Diego F. Manotas-Duque [a,2], Jorge M. Uribe [b,3]

[a] Universidad del Valle, Faculty of Engineering, School of Industrial Engineering, Colombia
[b] Faculty of Economics and Business, Universitat Oberta de Catalunya and IREA, University of Barcelona, Spain

ARTICLE INFO

JEL classification:
E44
G20
G21

Keywords:
Banks' ROA
Stress in financial markets
Dynamic factors
Financial cycles

ABSTRACT

We study banks' profitability in the US economy by means of dynamic factor models. Our results emphasize the importance of a few common cyclical market factors that greatly determine banking profitability. We conduct exhaustive regressions in a big data set of macroeconomic variables aiming to gain interpretability of our statistical factors. This allows us to identify three main macroeconomic factors underlying banking profitability: the financial burden of households and economic activity; household income and net worth and, in the case of ROA and ROE, stress in financial markets. We also provide an integrated perspective to analyse banks' profitability dynamically and to inform policymakers concerned with financial stability issues, for which banks' profitability is fundamental. Our models allow us to provide several rankings of vulnerable financial institutions considering the common market forces that we estimate. We emphasize the usefulness of such an exercise as a market-monitoring tool.

1. Introduction

Understanding the sources of profitability in the banking sector is of prime importance to both policymakers and professionals in the banking industry. On the one hand, the profitability of banks is under intense and constant scrutiny by regulators and central banks because it is directly related to the soundness of financial institutions and, therefore, to financial stability and the probability of systemic risk materialization. On the other hand, profitability is a targeted indicator by managers and CEOs who determine the optimal combinations of operating assets and capital sources, hoping to increase a bank's value and its return on investment. It is not surprising that there is a lively debate in the literature about whether profitability in banks is mainly due to idiosyncratic characteristics of financial institutions, such as size, scope, capitalization, asset quality, efficiency, and the business model, or, in contrast, is more a reflection of underlying common market forces, over which bank managers lack any kind of influence, such as short-term policy rates, long-term rates, general financial conditions, or more broadly speaking, cycles in economic activity (see Section 2). In practice, naturally, profitability answers to both sides of the narrative, but the key point is the degree to which one can rely on each side to explain the banking system performance (see Fig. 1).

In the first part of our study, we directly address this question. We answer how much of the profitability of the largest banks in the

* Corresponding author.
E-mail addresses: orlando.joaqui@correounivalle.edu.co (O. Joaqui-Barandica), diego.manotas@correounivalle.edu.co (D.F. Manotas-Duque), juribeg@uoc.edu (J.M. Uribe).
[1] ORCID: https://orcid.org/0000-0001-8190-0518.
[2] ORCID: https://orcid.org/0000-0003-0148-9840.
[3] ORCID: https://orcid.org/0000-0002-5844-2771.

https://doi.org/10.1016/j.najef.2022.101714
Received 19 January 2022; Received in revised form 26 May 2022; Accepted 31 May 2022
Available online 2 June 2022
1062-9408/

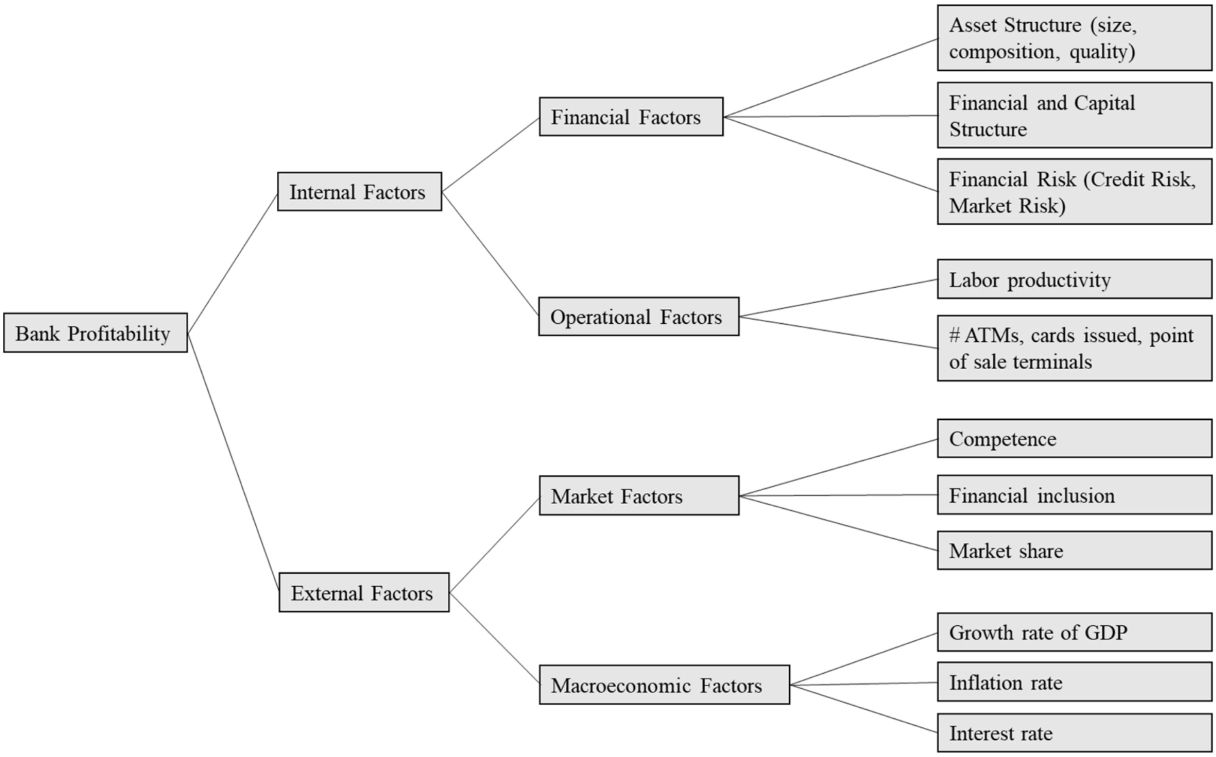

Fig. 1. Lines of analysis of bank profitability. **Note:** This figure identifies in the literature on bank profitability two lines of analysis related with the determinants of the banks performance: 1). Internal determinants and 2) External determinants.

US banking system can be explained by common underlying market forces, which are not related to idiosyncratic characteristics. We adopt an eclectic perspective based on dynamic factor models, often used in machine learning asset pricing but novel in the context of our research question. Our approach allows us to directly quantify how much of the profitability of the largest US banks can be explained by some common factors to which all financial institutions are directly exposed. Three statistical factors[4] are sufficient to explain between 63% and 68% of the returns on assets (ROA), returns on equity (ROE) and EBITDA margin variations for the US banking industry from 2002Q2 to 2020Q4. This is a significant fact, considering that in a hypothetical case in which banks' profitability is fully explained by bank-specific characteristics, these three factors can be expected to account for up to 1.2–2.5% of the total variation in our panel of profitability indicators, which concern more than a hundred banks operating in the US market (in some cases up to 241). This first result is in line with the fact already documented in the literature and well known by central banks and practitioners that banking is a very cyclical industry and therefore dominated by underlying market macroforces, which determine most of the dynamics of a bank's performance. We offer a way to quantify to what extent this occurs.

In the second part, we go a step further by considering the interpretation of our statistical factors, estimated by regularized principal components analysis (PCA). This is actually a tough question, as PCA and machine learning in general are often criticized on the grounds of interpretability. In summary, to achieve reliable results when modelling a given economic (or other) phenomenon, it is often not enough to capture the statistical dynamics within the system, but we also need to understand what reasons underlie the reported empirical results if we aim to convincingly generalize our conclusions beyond the study sample. This problem brings us closer to the banking literature that has examined the macroeconomic determinants that impact bank profitability, such as GDP growth or market-wide liquidity. Unlike these studies, we follow a novel big data approach to address the problem. Rather than establishing in advance the macroeconomic factors responsible for the profitability of banks, which inevitably increases the risk of missing important confounding covariates unknown to the literature or the researcher, we let the data speak as freely as possible. Our approach consists of the following two steps. First, we collect and preprocess 248 quarterly series of US economic activity recently assembled by McCracken and Ng (2021), which together constitute a complete picture of real markets, financial markets and prices in the US. Then, we relate each of our three statistical factors to each series in the set of big data macro variables and select the heaviest loading series among them, using marginal R-squared statistics from exhaustive and separated regressions and thereby matching our statistical factors with well-known economic series that can be easily interpreted.

In this regard, we are inspired by McCracken and Ng (2021), who use statistical factors extracted from the same big data set of macrolevel variables as ours and then identify the strongest loading series using marginal R-squares among the original variables. This

[4] The optimal number of factors was decided following the criterion proposed by Bai and Ng (2002).

avenue confers interpretability to their results and ours. However, although similar in spirit to our approach, our statistical factors are estimated *outside* the macro system, i.e., from our banking profitability data. Therefore, there is no *a priori* reason to expect a high correlation between the factors and the individual series. Bearing this in mind, we are still able to identify what series drive the dynamics of each banking profitability factor, which makes our results solid and insightful. The first factor is related to the financial burden of households and economic activity, the second factor is associated with household income and, hence, employment, and the third factor is related to stress in financial markets (this factor involves changes in EBITDA, in which case it is closer to the dynamics of housing markets). Interestingly, our banking factors do not perfectly (or even closely) match three additional factors estimated using the macroeconomic series related to economic activity, prices and financial conditions. The largest correlation (in magnitude) among the banking and macroeconomic factors is -0.44, appearing between the second banking factor (household income) and the third macroeconomic factor (financial conditions). Otherwise, the two sets of factors depict largely independent trajectories, which highlights the advantages of our approach against the alternative path of identifying the market factors directly from the set of macroeconomic series.

In the third part of our results, we turn to the bank-specific side of the narrative. Having identified the main systemic forces behind the profitability of all banks and established their dominance to explain the cross-sectional profitability of banks, we investigate each bank's exposure to each factor and explore the explanatory power of our three-factor model on an individual basis. In this way, we can provide a ranking of banks according to their sensitivity to the three underlying market forces. The explanatory power of our factor model lies between a minimum of 6% and a maximum of 93%, with an interquartile range of 43%-77%. This highlights the heterogeneity of banks' exposure to the three market forces and the general adequacy of the proposed methodology to monitor banking profitability. We emphasize that ours is not necessarily an exercise in systemic risk, since we do not focus on particularly bad situations (for example, the lowest quantiles of profitability), but rather we analyse the average scenarios using average factors. However, we do gain novel insights in terms of systemic risk in this part of our results. We find that while the profitability dynamics of certain banks may be unrelated to certain systemic forces (e.g., the first and second banking factors), they may be highly linked to others (e.g., the third banking factor). The results here highlight the convenience of monitoring banks' profitability by using an integrated approach along the lines that we propose instead of by resorting to various indicators provided in the literature, such as the widely known approaches by Acharya et al. (2012) or Adrian and Brunnermeier (2016). Such indicators, despite reflecting different sides of systemic risk, are not mutually exclusive; therefore, they are highly correlated with each other. Our profitability indicators are directly identified as orthogonal combinations (i.e., PCA), such that they offer the integrated and complementary perspective that we emphasize.

Our results are robust to changing the method to estimate the factors from the baseline regularized PCA to traditional PCA and other methodological choices, to dividing our sample according to the market capitalization of the banks within the study sample (although the results seem more binding for the largest banks) and to using the three main indicators of profitability, namely, ROA, ROE and EBITDA (although the last factor has a different influence on EBITDA), which are additionally sampled at different frequencies, quarterly in the first two cases and annually in the last case. One of the main contributions of our study is that we establish that when researchers and managers examine bank profitability, they must control for macroeconomic variables. For example, it is important to control for variables such as household liabilities, manufacturing, average weekly hours of production, or credit spreads. These variables are shown to be relevant proxies for the common variation of banking profitability. Our results also emphasize the high commonality of banking profitability. Banks with a larger exposure to such commonality can be said to be more sensitive to scenarios of systemic risk materialization.

The rest of this document is organized as follows. In the second part, we review in more detail the related literature and put our contribution into perspective. In the third part, we describe our methods. In the fourth section, we present our data and main results and provide some robustness for our claims, while in the fifth and last section, we conclude and offer some future research avenues.

2. Bank profitability literature

Bank profitability analysis has been one of the most important financial economics research challenges over time. There are different streams of the literature that analyse bank profitability. It is possible to identify in the literature two lines of analysis related to the determinants of the performance of financial institutions.

First, we find internal determinants, such as the structure and size of assets and the financial and capital structure of financial institutions. In this same group, internal determinants of operational character are analysed, such as the productivity of the workforce and the number of ATMs and customer service offices.

Le and Ngo (2020) investigate the determinants of bank profitability in 23 countries from 2002 to 2016. The main findings of this study point out operational determinants, such as the number of bank cards issued, the number of automated teller machines and the number of points of sale terminals, all of which can increase bank profitability. Additionally, these authors suggest that market power has a negative impact on bank profitability, and a more concentrated banking system is associated with lower profitability because nonprice competition may be more intense in more concentrated markets. Furthermore, managers can more easily engage in expense-preference behaviour so bank costs in such markets are higher, thus lowering profitability; in contrast, competition increases it. Other authors, such as Kumar et al. (2021), focus their analysis on bank profitability on topics related to financial inclusion. The main conclusions of this study suggest that banks with a wider scope of financial services are more profitable than their counterparts. Other key issues studied by these authors define cost management, credit risk management and bank size as key drivers of bank profitability.

Duan and Niu (2020) propose another path of research focalized on the analysis of liquidity creation and bank profitability. These authors highlight that liquidity creation, related to the liability side, enhances bank profitability, while asset-side liquidity creation reduces bank profitability. Other authors who have studied the relationship between liquidity and bank profitability are Fernandes

Table 1
Summary statistics of financial indicators.

ROE
N = 111 T = 75 Q

	Mean (%)	Sd (%)	Median (%)	Skewness	Kurtosis	Min (%)	Max (%)
All	9.67	2.98	9.63	0.03	0.96	0.59	18.05
Small	9.48	3.15	9.63	−0.42	0.54	0.59	15.35
Medium	9.70	3.01	9.61	0.35	2.40	2.15	18.05
Big	9.82	2.86	9.94	0.32	0.26	3.89	16.84

ROA
N = 118 T = 75 Q

	Mean (%)	Sd (%)	Median (%)	Skewness	Kurtosis	Min (%)	Max (%)
All	0.82	0.23	0.81	0.22	0.87	0.21	1.51
Small	0.81	0.25	0.82	−0.15	0.34	0.21	1.37
Medium	0.81	0.22	0.80	0.14	1.19	0.35	1.36
Big	0.86	0.22	0.83	0.91	1.29	0.51	1.51

EBITDA margin
N = 241 T = 20 Y

	Mean (%)	Sd (%)	Median (%)	Skewness	Kurtosis	Min (%)	Max (%)
All	36.83	14.46	37.87	−1.89	11.16	−64.79	79.29
Small	32.59	14.86	33.86	−0.54	1.85	−18.18	71.89
Medium	38.36	14.52	39.61	−4.57	32.13	−64.79	61.87
Big	39.86	12.88	39.84	−0.63	4.38	−10.77	79.29

Note: Statistics estimated as mean, standard deviation (Sd), median, min, max, are presented as percentages (%). N denotes the number of banks used in each type of financial indicator. T denotes the number of periods in the sample, with Q: Quarter Y: Years.

Table 2
Summary of variance explained by banking factors according to market cap and financial indicator.

		ROE	ROA	Margin EBITDA
		N = 111 T = 75Q	N = 118 T = 75Q	N = 241 T = 20Y
	Banking Factor	Exp. Variance (%)	Exp. Variance (%)	Exp. Variance (%)
All	F1	46.3	54.7	38.3
	F2	11.6	7.9	20.1
	F3	5.5	5.6	9.1
	Total	63.4	68.2	67.5
Small	F1	38.6	47.7	34.6
	F2	12.1	10.2	19.6
	F3	7.2	6.4	10.8
	Total	57.9	64.3	65.0
Medium	F1	52.4	58.0	39.6
	F2	12.2	8.2	17.8
	F3	5.4	5.4	10.9
	Total	70.0	71.6	68.3
Large	F1	50.8	61.7	48.7
	F2	11.5	7.5	19.7
	F3	6.7	5.2	6.6
	Total	69.0	74.4	75.0

Note: F1, F2, F3, specifically denote the estimated banking factors by the (regularized) iterative PCA algorithm. N denotes the number of banks used in each type of financial indicator. T denotes the number of periods in the sample, with Q: Quarter Y: Years.

et al. (2021). They examine the effect of cash holdings on bank profitability using a worldwide database. Their results show that there is a nonmonotonic relationship between the cash conversion cycle and bank profitability. Athanasoglou et al. (2008) provide evidence on the significance of internal determinants of profitability such as capital, credit risk, size, operating expense management, and also on external determinants such as inflation expectations and cyclical production. Demirgüç-Kunt and Huizinga (1999) also analyze the internal and external determinants of bank profitability. They show that bank characteristics like capital, loans, customers, and short-

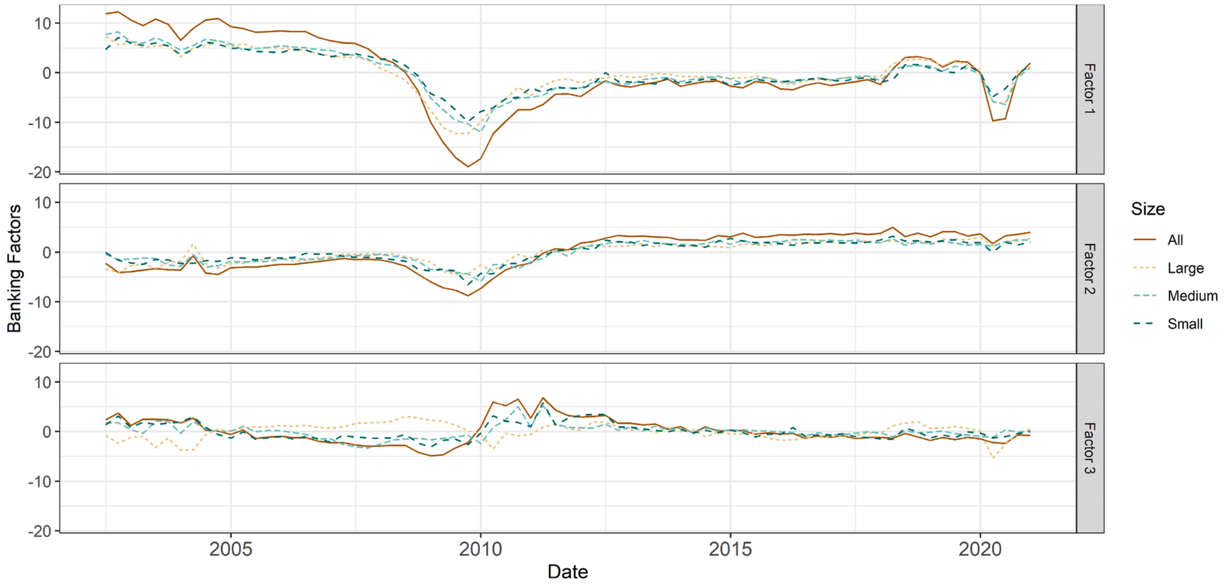

Fig. 2. Banking factors from ROE. **Note:** This figure shows the three banking factors for the total sample (solid line) and divided according to the banks' size (dotted lines). These factors are estimated from the ROE information of 111 banks, using the iterative (regularized) PCA algorithm.

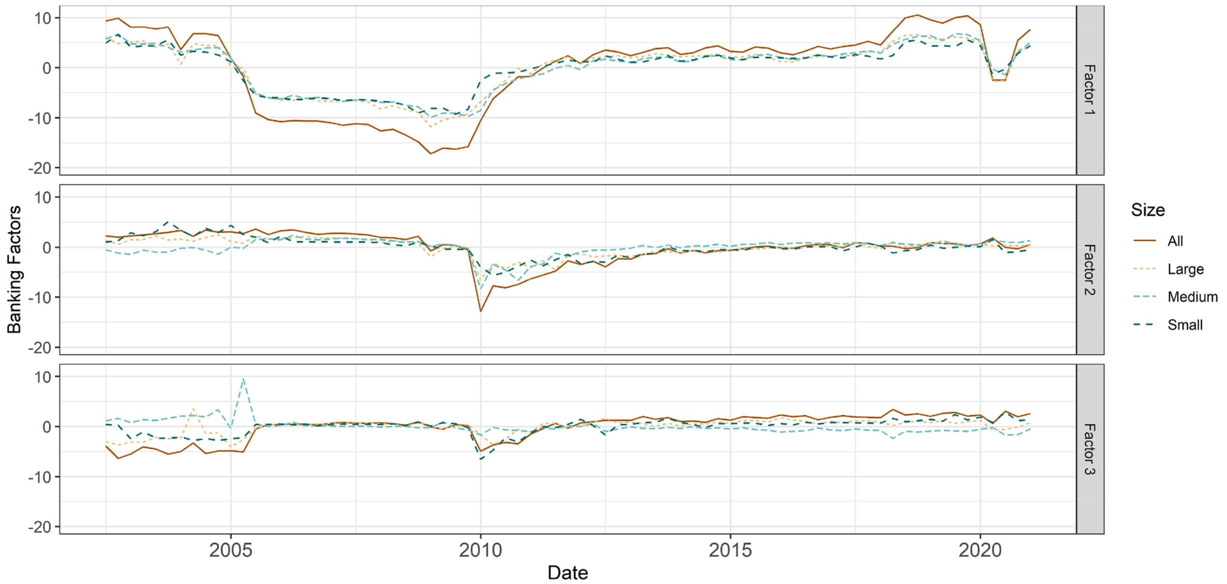

Fig. 3. Banking factors from ROA. **Note:** This figure shows the three banking factors for the total sample (solid line) and divided according to the banks' size (dotted lines). These factors are estimated from the ROA information of 118 banks, using the iterative (regularized) PCA algorithm.

term financing influence bank profitability. In addition, they identify significant external characteristics such as GDP per capita, real interest rate, and inflation.

The second stream of research focuses on the relationship of external factors and bank profitability. This group of factors includes fundamental macroeconomic determinants and market factors, such as competence and market share (Akhter & Daly, 2009; Bolt et al., 2012; de Mendonça & da Silva, 2018; Kanas et al., 2012; Mohanty et al., 2021).

Regarding this macroeconomic environment, Kanas et al. (2012) show that the profitability of banks is affected by the economic cycle, short-term interest rates, inflation expectations, credit risk, and the effect of the structure of the loan portfolio on profits. Similar results are reported by Martins et al. (2019) for real estate banks in the United States, the United Kingdom, and Germany, where they point out that profitability depends on macroeconomic characteristics, such as volatility of interest rates and GDP. Along the same lines, Alessandri and Nelson (2015) show that in the long term, high interest rates present a positive relationship with profitability and bank margins; Molyneux et al. (2019), on their side, show that bank yields fell due to the rise of negative interest rates, although this

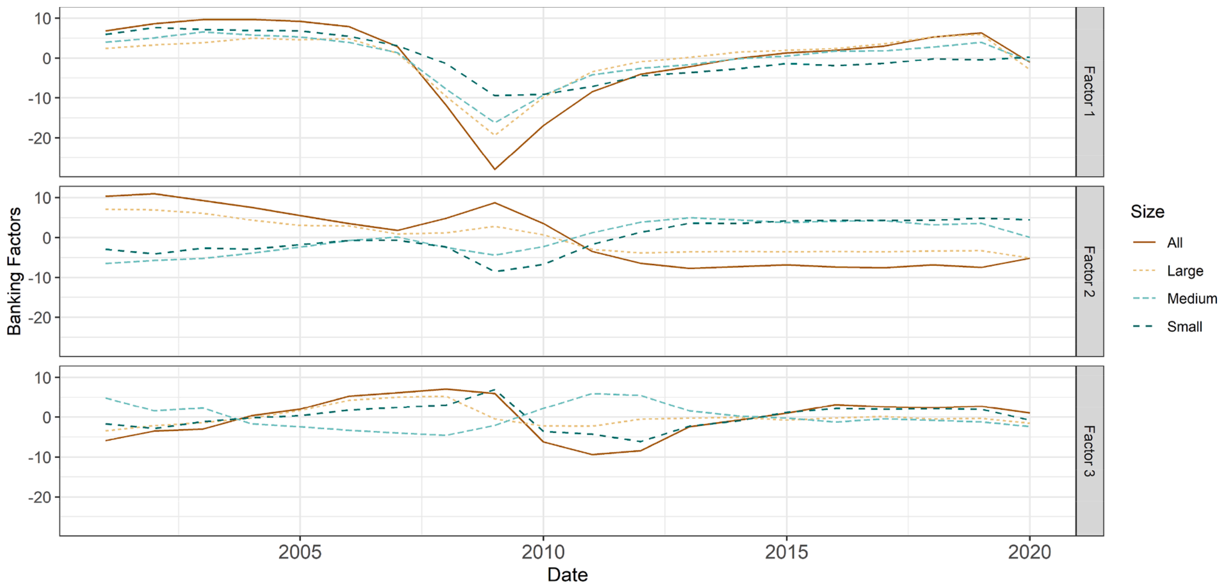

Fig. 4. Banking factors from EBITDA. **Note:** This figure shows the three banking factors for the total sample (solid line) and divided according to the banks' size (dotted lines). These factors are estimated from the EBITDA information of 241 banks, using the iterative (regularized) PCA algorithm.

Fig. 5. Macroeconomic factors from FRED-QD. **Note:** This figure shows the three macroeconomic factors for the total of 248 macroeconomic series from FRED-QD database, using the iterative (regularized) PCA algorithm.

effect also depended on the bank's structure and factors such as size and financing sources.

Studies have explored different relationships between the cyclical determinants of bank profitability and a variety of financial and monetary variables (e.g., Borio et al., 2017; Detragiache et al., 2018; Elekdag et al., 2020; Molyneux & Thornton, 1992). Some studies have focused their attention on the effects of macroeconomic dynamics on the profitability of banks in the European Union (Albertazzi & Gambacorta, 2009; Dietrich & Wanzenried, 2011; Djalilov & Piesse, 2016; Pasiouras & Kosmidou, 2007). Guerrieri and Harkrader (2021) also study the effect of macroeconomic factors on banking profitability. Unlike us, these authors extract the common factors that describe a large set of macroeconomic series, and then use the macro-factors to explain the profitability of each bank. In our case, the profitability factors are directly extracted from the profitability data, and only after this, interpreted in terms of a large dataset of macroeconomic series. For this reason, unlike them, we are able to quantify the level of commonality in the profitability series. The two approaches also differ in more fundamental ways. For instance, regarding the identification of the systematic and idiosyncratic components in the factor model of banking profitability. Guerrieri and Harkrader (2021) assume that their estimated macroeconomic factors are the common factors driving the panel of banking indicators, and consistently bank-specific components are the residuals of a regression of each bank performance on the macro factors. On the contrary, we follow a traditional factor model in econometrics (Bai

Table 3
Top 5 of FRED's macroeconomic variables that best explain banking factors using ROE.

Banking Factors	Group	Description	R^2_{Adj}
All			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.66
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.52
	Industrial Production	Capacity Utilization: Total Industry (Percent of Capacity)	0.45
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.39
	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.34
Factor 2	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.67
	Employment and Unemployment	Help-Wanted Index	0.59
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.34
	Employment and Unemployment	All Employees: Financial Activities (Thousands of Persons)	0.23
	Employment and Unemployment	All Employees: Construction (Thousands of Persons)	0.23
Factor 3	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.33
	Non-Household Balance Sheets	Nonfinancial Noncorporate Business Sector Liabilities to Disposable Business Income (Percent)	0.31
	Money and Credit	FRB Senior Loans Officer Opions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans	0.31
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.30
	NIPA	Real government state and local consumption expenditures (Billions of Chained 2012 Dollars), deflated using PCE	0.27

Note: This table presents the macroeconomic series of the FRED-QD most correlated with each of the banking factors estimated according to the R^2_{Adj} criterion. Each of the series is classified into a group determined by Stock and Watson (2012).

& Ng, 2008), to disentangle the idiosyncratic from the systematic variation and, consistently, apply PCA to the series of banking profitability. In this way, we guarantee that our factors are consistent estimates of the common variation in the profitability series. In other words, the optimal weights that constitute the macro-factors in Guerrieri and Harkrader (2021) are suboptimal to describe the profitability series, while our profitability-factor are optimal by construction.

We fill an important gap in the literature by exploring all possible sources of macroeconomic profitability from a big data perspective. Our approach builds and expands on insights of past literature that link bank profitability with the macroeconomy.

3. Methodology

Our methodology consists of four sections. First, we present dynamic factor models as described by Bai and Ng (2002), which are used to explain the unobservable market-wide forces that determine banking profitability. Second, we present the statistical criteria used to determine the number of factors that suffice to construct our models. Third, we present our factor estimation method based on regularized PCA (Josse and Husson, 2012). Finally, in the fourth section, we show how we can gain insight into the factor's interpretability using the marginal coefficient of determination R^2_{Adj} from linear regressions of the estimated banking factors on a comprehensive set of macroeconomic series.

3.1. Dynamic factor models

A factor model is used to quantitatively measure the sensitivity of banks to unobservable systemic forces. We also establish how much of the dynamics of bank profitability are due to the idiosyncratic characteristics of banks and to common systemic forces.

We adapt our exposition from Bai and Ng (2002) and Bai and Ng (2008). Let y_{it} be the observed profitability data (either ROE, ROA, and EBITDA) for the i-th unit of the cross-section (i.e., bank) at time t, for $i = 1, \cdots, N$ and $t = 1, \cdots, T$. Consider the following model:

$$y_{it} = \lambda_i^{'}\mathrm{F}_t + e_{it}y_{it} = C_{it} + e_{it}, \tag{1}$$

where F_t is a vector of common factors, e_{it} is the idiosyncratic component of y_{it} and λ_i is a vector of factor loads associated with F_t. This is a vector of weights that unit i places on the corresponding r static common factors F_t. The term $C_{it} = \lambda_i F_t$ refers to the common

Table 4
Top 5 of FRED's macroeconomic variables that best explain macroeconomic factors.

Macroeconomic Factors	Group	Description	R^2_{Adj}
Factor 1	NIPA	Manufacturing Sector: Real Output (Index 2012 = 100)	0.91
	Industrial Production	Industrial Production: Manufacturing (SIC) (Index 2012 = 100)	0.91
	NIPA	Real Gross Domestic Product, 3 Decimal (Billions of Chained 2012 Dollars)	0.91
	NIPA	Business Sector: Real Output (Index 2012 = 100)	0.91
	Employment and Unemployment	Nonfarm Business Sector: Hours of All Persons (Index 2012 = 100)	0.90
Factor 2	Prices	Producer Price Index by Commodity Intermediate Materials: Supplies & Components (Index 1982 = 100)	0.57
	Prices	Personal Consumption Expenditures: Chain-type Price Index (Index 2012 = 100)	0.57
	Prices	Personal consumption expenditures: Goods (chain-type price index)	0.57
	Prices	Consumer Price Index for All Urban Consumers: Commodities (Index 1982–84 = 100)	0.57
	Prices	Consumer Price Index for All Urban Consumers: All items less shelter (Index 1982–84 = 100)	0.57
Factor 3	Stock Markets	CBOE S&P 100 Volatility Index: VXO	0.52
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Assets (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.49
	Household Balance Sheets	Real Total Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.48
	Household Balance Sheets	Real Net Worth of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.47
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Net Worth (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.47

Note: This table presents the macroeconomic series of the FRED-QD most correlated with each of the macroeconomic factors estimated according to the R^2_{Adj} criterion. Each of the series is classified into a group determined by Stock and Watson (2012).

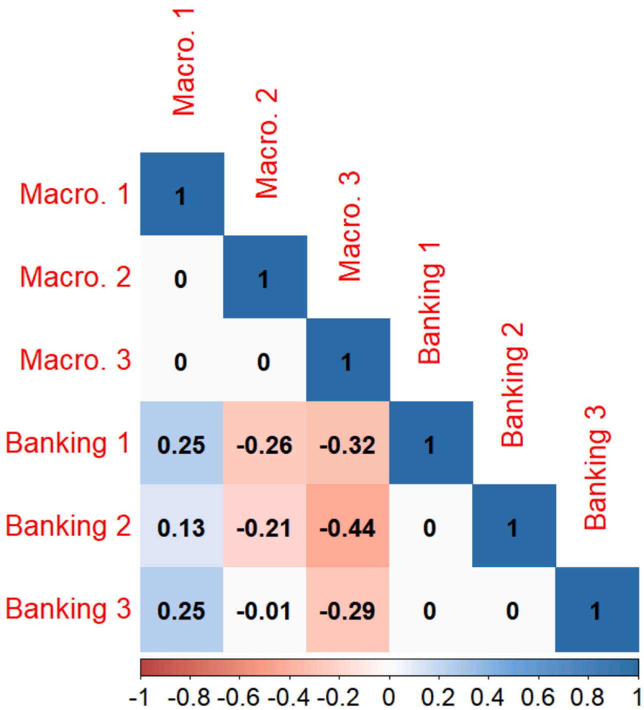

Fig. 6. Banking and macroeconomic factor correlations. **Note:** This figure shows the correlation between the banking factors and the estimated macroeconomic factors. The intensity of the color shows the strength of association between the factors. The blue color denotes direct or positive association, while the red color denotes inverse or negative association. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

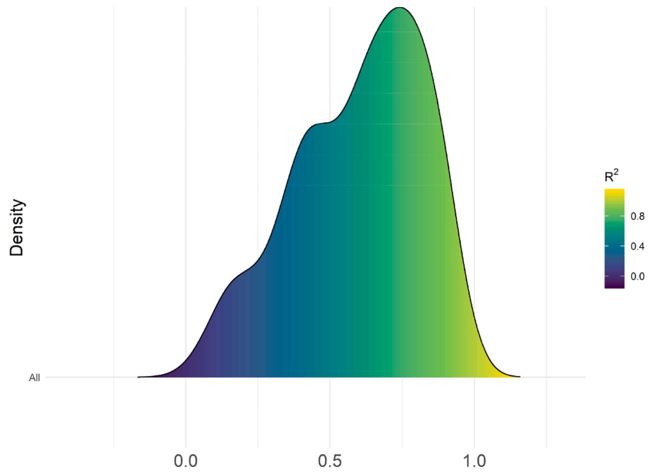

Fig. 7. Distribution of R^2 of the model by factors. **Note:** This figure shows the density about $\boldsymbol{R^2_{Adj}}$ for the set of regressions of the dynamic factor models from ROE.

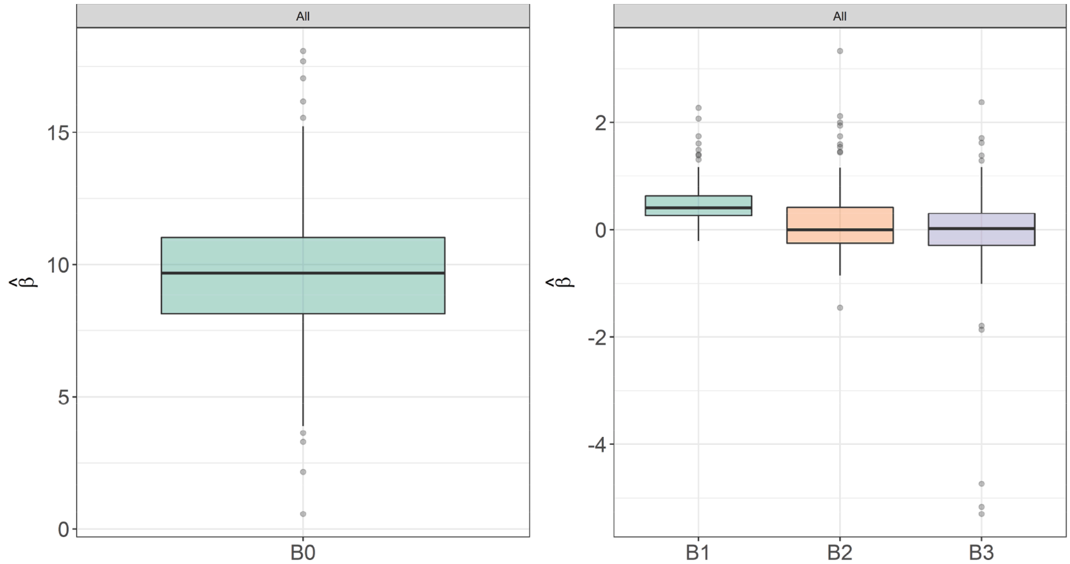

Fig. 8. Distribution of model estimators by factors. **Note:** The left panel shows the distribution of the $\boldsymbol{\beta}_0$ estimator that represents the fixed effect. The right panel shows the distribution of the estimates of the effect $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$ of the banking factors. Where $\boldsymbol{\beta}_1$ measures a bank's sensitivity to household burden and capacity utilization. $\boldsymbol{\beta}_2$ constitutes a risk indicator associated with household income and $\boldsymbol{\beta}_3$ represents an indicator of risk obeying stress in financial markets.

Table 5
Summary statistics of estimators.

Statistic	β_0	β_1	β_2	β_3
Min	0.57	−0.22	−1.45	−5.30
Q1	8.14	0.26	−0.26	0.30
Median	9.68	0.41	0.00	0.02
Q3	11.03	0.63	0.42	0.31
Mean	9.67	0.52	0.18	−0.07
St. Dev.	3.05	0.42	0.71	1.04
Max	18.08	2.27	3.33	2.38

Note: This table presents summary statistics for each one effects estimated. The statistics: minimum, maximum, mean, median, standard deviation, quantiles 25th and 75th are in percentage.

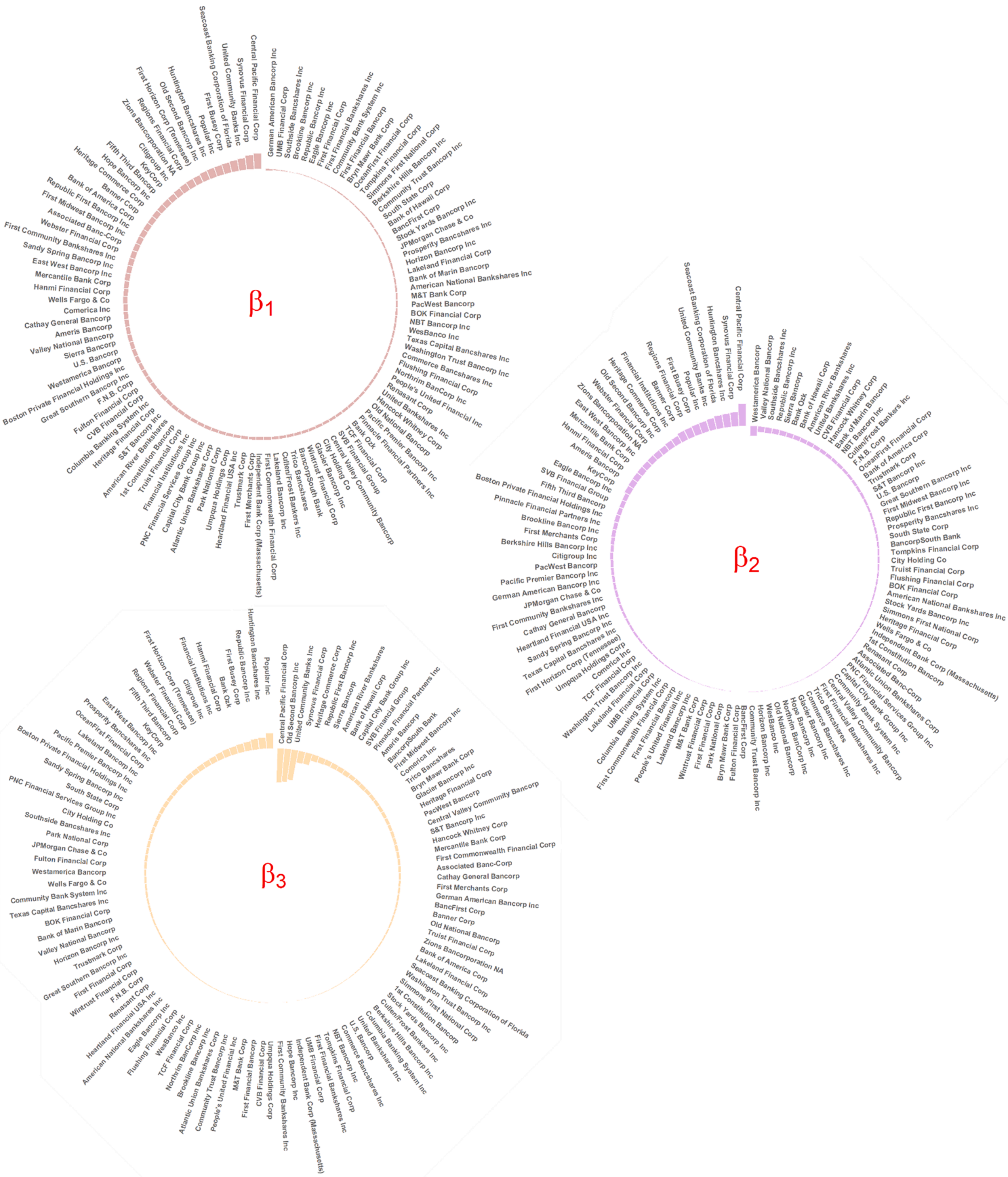

Fig. 9. Total ranking of banks by risk indicators. **Note:** Each spiral shows the ranking of the banks with respect to the estimate of the effect of each banking factor. The ranking starts clockwise with the least vulnerable banks in each factor and ends with the most vulnerable banks in each factor. If the bar points towards the inside of the chart, it is because the estimate is negative.

Table 6
Top 10 banks according to the estimated parameters of the model by factors using ROE.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Westamerica Bancorp	0.927	Bank of Hawaii Corp	18.08	Central Pacific Financial Corp	2.27	Central Pacific Financial Corp	3.33	Popular Inc	2.38
2	Webster Financial Corp	0.921	Westamerica Bancorp	17.69	Synovus Financial Corp	2.07	Synovus Financial Corp	2.12	Huntington Bancshares Inc	1.71
3	Fulton Financial Corp	0.904	Bank Ozk	17.06	United Community Banks Inc	1.74	Huntington Bancshares Inc	2.00	Republic Bancorp Inc	1.62
4	Trustmark Corp	0.900	U.S. Bancorp	16.18	Seacoast Banking Corporation of Florida	1.60	Seacoast Banking Corporation of Florida	1.94	First Busey Corp	1.38
5	Synovus Financial Corp	0.898	City Holding Co	15.55	First Busey Corp	1.49	United Community Banks Inc	1.74	Bank Ozk	1.29
6	Hope Bancorp Inc	0.887	Stock Yards Bancorp Inc	15.24	Popular Inc	1.40	Popular Inc	1.59	Hanmi Financial Corp	1.17
7	East West Bancorp Inc	0.885	First Financial Bankshares Inc	14.24	Huntington Bancshares Inc	1.39	First Busey Corp	1.54	Financial Institutions Inc	1.15
8	Truist Financial Corp	0.884	Southside Bancshares Inc	13.73	Old Second Bancorp Inc	1.31	Regions Financial Corp	1.45	Citigroup Inc	1.04
9	Cullen/Frost Bankers Inc	0.884	Great Southern Bancorp Inc	13.62	First Horizon Corp (Tennessee)	1.17	Banner Corp	1.44	First Horizon Corp (Tennessee)	0.91
10	Zions Bancorporation NA	0.883	CVB Financial Corp	13.52	Regions Financial Corp	1.17	Financial Institutions Inc	1.16	Webster Financial Corp	0.85
Lower ranking of banks										
1	South State Corp	0.065	Central Pacific Financial Corp	0.57	German American Bancorp Inc	−0.22	Westamerica Bancorp	−1.45	Central Pacific Financial Corp	−5.30
2	Republic Bancorp Inc	0.134	United Community Banks Inc	2.17	UMB Financial Corp	−0.11	Valley National Bancorp	−0.85	Old Second Bancorp Inc	−5.16
3	First Financial Corp	0.138	Seacoast Banking Corporation of Florida	3.29	Southside Bancshares Inc	−0.08	Southside Bancshares Inc	−0.82	United Community Banks Inc	−4.73
4	Bryn Mawr Bank Corp	0.144	Republic First Bancorp Inc	3.63	Brookline Bancorp Inc	−0.04	Republic Bancorp Inc	−0.74	Synovus Financial Corp	−1.87
5	UMB Financial Corp	0.158	Synovus Financial Corp	3.89	Republic Bancorp Inc	0.06	Sierra Bancorp	−0.72	Heritage Commerce Corp	−1.79
6	People's United Financial Inc	0.160	Banner Corp	4.46	Eagle Bancorp Inc	0.08	Bank Ozk	−0.67	Republic First Bancorp Inc	−1.01
7	Pacific Premier Bancorp Inc	0.180	Old Second Bancorp Inc	4.62	First Financial Corp	0.08	Bank of Hawaii Corp	−0.64	Sierra Bancorp	−0.91
8	First Financial Bancorp	0.185	Regions Financial Corp	5.40	First Financial Bankshares Inc	0.10	American River Bankshares	−0.60	American River Bankshares	−0.79
9	Berkshire Hills Bancorp Inc	0.231	Popular Inc	5.45	Community Bank System Inc	0.11	United Bankshares Inc	−0.60	Bank of Hawaii Corp	−0.79
10	Heritage Commerce Corp	0.239	Berkshire Hills Bancorp Inc	5.46	First Financial Bancorp	0.13	CVB Financial Corp	−0.56	Capital City Bank Group Inc	−0.74

Note: This table presents the consolidation of the top 10 banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

component of the model. From Equation (1), letting $Y_t = (y_{1t}, y_{2t}, \cdots, y_{Nt})'$, $F = (F_1, F_2, \cdots, F_T)'$ and $\Lambda = (\lambda_1, \cdots, \lambda_N)'$ in vector form, we have:

$$Y_t = \Lambda F_t + e_t, \tag{2}$$

Even though the model identifies a static relationship between y_{it} and F_t, F_t itself can be a dynamic vector process that evolves according to $A(L)F_t = u_t$, where $A(L)$ represents a polynomial of the lag operator. The idiosyncratic error e_{it} can also be a dynamic process. The static model can be compared with the dynamic factor model defined as follows:

$$y_{it} = \lambda_i'(L)f_t + e_{it}, \tag{3}$$

Table 7
Comparison of the estimation of banking factors according to multivariate analysis.

	Banking Factor	ROE N = 111; T = 75 Q Exp. Variance (%)	ROA N = 118; T = 75 Q Exp. Variance (%)	Margin EBITDA N = 241; T = 20 Y Exp. Variance (%)
Method 1:	F1	46.3	54.7	38.3
The (regularized) iterative PCA algorithm	F2	11.6	7.9	20.3
	F3	5.5	5.6	9.2
	Total	63.4	68.2	67.8
Method 2:	F1	42.1	52.5	38.1
PCA classic	F2	10.6	7.6	19.0
(NA = 0)	F3	5.1	4.7	9.2
	Total	57.9	64.8	66.5
Method 3: NIPALS algorithm	F1	44.8	54.7	38.4
	F2	11.1	7.6	19.5
	F3	5.3	4.7	9.1
	Total	61.4	67.0	67.1
Method 4:	F1	35.1	41.1	6.9
Factor-Based Imputation for Missing Data	F2	8.6	5.7	3.7
	F3	3.8	3.0	1.7
	Total	47.6	49.8	12.3

Note: Each result in the table shows the percentage of variance explained by each factor estimated according to the multivariate analysis methodology. N denotes the number of banks used in each type of financial indicator. T denotes the number of periods in the sample, with Q: Quarter Y: Years.

where $\lambda_i(L) = (1 - \lambda_{i1}L - \cdots - \lambda_{is}L^s)$ is a vector of dynamic factor loadings of order s. When s is finite, we have a dynamic factor model. The law of motion governing the factor dynamics is given by:

$$f_t = C(L)\varepsilon_t,$$

where ε_t are *iid* errors. The dimension of f_t is the same dimension as ε_t, and it refers to the number of dynamic factors, denoted by q. Dynamic factor models with finite s are represented as static factor models with r finite; however, the dimension of F_t is often different from the dimension of f_t because F_t includes the lags and leads of f_t with $r \geq q$ (Bai & Ng, 2007). More generally, if we have q dynamic factors, we obtain $r = q(s+1) \geq q$ static factors.

Under this specification, it is necessary to determine the optimal number of estimated banking factors $\widehat{\mathrm{F}}$. The factor loads associated with $\widehat{\mathrm{F}}$ do not change over time, and they quantify the risk associated with each of the estimated profitability factors. $\widehat{\lambda}_{0i}$ measures the part of the system's profitability, which is static and largely associated with a bank fixed effect. The larger the magnitude of this estimate, the less susceptible a bank is to fluctuating common variations. However, our main interest is to quantify how much of the system variation can be explained by common forces and how much by bank idiosyncrasies, so instead of analysing the intercepts of the model in Eq. (3), we need to focus our attention on the slope coefficients known as the factor loadings $\widehat{\lambda}_{1i}, \widehat{\lambda}_{2i}\cdots$ and the residual variation e_{it}.

3.2. Selecting the number of factors

A strategy frequently used to estimate the optimal number of factors (r) conforming to the low-dimensional factor structure of a given system is the graphical representation of the system's eigenvalues. Specifically, we could use the point where the graph changes slope as an estimate of r. In contrast, a more transparent and quantitative way to determine the number of factors in the system is to balance the cost of adding an additional factor with increasing model complexity, and it was proposed by Bai and Ng (2020). The number of optimal factors $\widehat{k}$ is obtained from the estimation of the corresponding factor loadings that accompany the observed factors, which can be consistently estimated from $\widehat{k} = \mathrm{arg}min_{0 \leq k \leq kmax} PC(k)$ with $r \leq kmax$. Let:

$$PC(k) = V\left(k, \widehat{F}^k\right) + kg(N,T), \tag{5}$$

where $PC(k)$ is the loss function. It is used to estimate $\widehat{k}$, where $g(N,T)$ is an overfitting penalty, $\widehat{F}^k$ is the matrix of k estimated factors and $V\left(k, \widehat{F}^k\right)$ denotes the sum of squared residuals, as specified in Eq. (6).

$$V\left(k, \widehat{F}^k\right) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda_i^{k'} \widehat{F}_t^k\right)^2, \tag{6}$$

Another criterion by which r can be estimated consistently is

$$IC(k) = \ln\left(V\left(k, \widehat{F}^k\right)\right) + kg(N,T), \tag{7}$$

The IC criterion thus resembles information criteria frequently used in time-series analysis, with the important difference that the penalty here depends on both N and T. It is often used in empirical work such as Bai and Ng (2019) and is obtained when.

$$g(N,T) = \frac{(N+T)}{NT}\log\left(\frac{NT}{N+T}\right). \tag{8}$$

In such a way, r can be determine by

$$\widehat{r} = \min_{k=0,\cdots,rmax} IC(k), \tag{9}$$

We also verify that our estimated number of factors agrees with the empirical recommendation of using a relatively low number of factors, i.e., between three to seven, when working with panels of similar size to ours (Bai & Ng, 2007; Chudik & Pesaran, 2015; Chuliá et al., 2017; Gilchrist et al., 2009; Stock & Watson, 2005). We also estimate the number of dynamic factors, q, in our system following the path traced back to Bai and Ng (2007).

3.3. The (regularized) iterative PCA algorithm

In the estimation of the banking profitability factors $\widehat{\mathrm{F}}$, we use the method of regularized principal components, due to Josse and Husson (2012). The objective is to determine a subspace that reduces the distances between individuals and their projections in this subspace. This is equivalent to finding two matrices $\mathrm{F}_{T\times S}$ and $\mathrm{U}_{N\times S}$ of rank S, with $S < T$, that provide the best approximation of the matrix of the original dataset $\mathrm{X}_{T\times N}$, with *T: Time* and *N: Banks*, in the least-squares sense, that minimize the following criteria:

$$\vartheta = ||\mathrm{X} - \mathrm{M} - \mathrm{FU}'||^2 = \sum_{t=1}^{T}\sum_{n=1}^{N}\left(X_{tn} - m_n - \sum_{s=1}^{S} F_{ts}U_{ns}\right)^2, \tag{10}$$

where M is a matrix of size $T\times K$ with each row equal to $(m_1,\cdots,m_N)$, i.e., the vector with the mean of each variable. A common technique that deals with missing values in PCA is to ignore missing values by minimizing the least-squares criterion in Eq. (10) overall non-missing entries. This can be achieved by introducing a weighted matrix W in the criterion, where $\mathrm{W}_{tn} = 0$ if X_{tn} is missing or $\mathrm{W}_{tn} = 1$ otherwise:

$$\vartheta = \sum_{t=1}^{T}\sum_{n=1}^{N} W_{tn}\left(X_{tn} - m_n - \sum_{s=1}^{S} F_{ts}U_{ns}\right)^2. \tag{11}$$

The iterative (regularized) PCA algorithm minimizes the criterion in Eq. (11). It consists of the following steps:

1- Initial values such as the mean of each variable are used to replace missing values.
2- The second step of the iterative (regularized) algorithm is conducting PCA using the complete data set. Then, you impute the missing values with the reconstruction formulas (regularized) of order *ncp* (the fitted matrix calculated with *ncp* components for the scores and loads (regularized)). The number of components used (*ncp*) for the imputation of missing data is calculated by cross-validation in such a way that the mean square error of prediction is minimized.
a) The optimal number of *ncp* components is estimated by cross-validation. The PCA is performed on the complete data set to estimate the parameters $\widehat{\mathrm{M}}^{\ell}, \widehat{\mathrm{F}}^{\ell}, \widehat{\mathrm{U}}^{\ell}$.
b) Missing values are imputed with adjusted values $\widehat{\mathrm{X}}^{\ell} = \widehat{\mathrm{M}}^{\ell} + \widehat{\mathrm{F}}^{\ell}\,\widehat{\mathrm{U}}^{\ell}$; the new imputed data set is $X^{\ell} = W{*}X + (1-W){*}\widehat{\mathrm{X}}^{\ell}$; here the missing values are replaced by the fitted values.
3- Steps are repeated 2-a) and 2-b) until convergence is achieved.

The output of the algorithm is used to estimate the banking factors $\widehat{\mathrm{F}} \equiv \widehat{\mathrm{F}}_{Bank}$ that determine the profitability of banks, where the solution satisfies the following two Eqs. (12) and (130:

$$\widehat{\mathrm{U}}' = (\widehat{\mathrm{F}}'\widehat{\mathrm{F}})^{-1}\widehat{\mathrm{F}}'(X - \widehat{\mathrm{M}}), \tag{12}$$

$$\widehat{\mathrm{F}}' = (X - \widehat{\mathrm{M}})\widehat{\mathrm{U}}(\widehat{\mathrm{U}}'\widehat{\mathrm{U}})^{-1}. \tag{13}$$

3.4. Interpreting the factors via marginal R-squared

We explore interpretability of the estimated factors, $\widehat{\mathrm{F}}_{Bank_p}$ with $p = 1,2,3$. To this end, we used FRED-QD database comprising of 248 macroeconomic series, we denote each series by MS_k, where $k = 1,\cdots,248$. The objective is to establish, based on the marginal determination coefficient of exahustive regressions, the top 5 macroeconomic variables that best explain each banking factor i. We then have 248 values of R^2_{Adj} extracted from each k model:

$$\widehat{\mathrm{F}}_{Bank_p} = \gamma_0 + \gamma_1 MS_k + u_k, \tag{14}$$

This procedure is carried out for the complete sample of banks for each financial indicator, as well as conditioning on bank size.

4. Data

Our data for US banking profitability and the macroeconomic environment come from two different sources. In the case of banking information, the data used were obtained from the Refinitiv database and correspond to profitability information measured through ROE (return on equity), ROA (return on assets), and EBITDA margin. ROA and ROE are sampled quarterly from 2002Q2–2020Q4. Profitability indicators are defined as follows. Return On Assets is calculated by dividing a company's net income prior to financing costs by its total assets. Return On Equity is calculated by dividing a company's net income by its total equity of common shares. EBITDA margin represents the ratio of Earnings before Interest, Taxes, Depreciation & Amortization (EBITDA) divided by the value of Revenue from Business Activities multiplied by 100. The denominator must be positive, otherwise excluded. Hence, we have 111 banks for ROA and 118 for ROE. In the case of EBITDA margin, our data are sampled annually from 2001 to 2020 for a total of 241 banks. The number of banks differs by financial indicator since banks that presented more than 10 quarters with missing values were discarded. In addition to the profitability data, market capitalization data were retrieved from Refinitiv. This variable was used to divide the banks according to their size: small, medium, and large, corresponding to banks with market capitalization between the minimum and the 33rd percentile, 33rd and 66th percentiles, and the 66th percentile to the maximum of the cross-sectional distribution, as of March 2021.

We used FRED-QD macroeconomic database provided by McCracken and Ng (2021). This dataset is publicly available and maintained by the Federal Reserve of St. Louis, through FRED. It consists of 248 series with quarterly frequency starting in 1959Q1. Many of these series have been aggregated from monthly series used in previous works by McCracken and Ng (2016), where they advance a collection of 128 macroeconomic series. These macroeconomic series are classified into 14 groups following Stock and Watson (2012): NIPA (National Income and Product Accounts), Industrial Production, Employment and Unemployment, Housing, Inventories, Orders and Sales, Prices, Earnings and Productivity, Interest Rates Money and Credit, Household Balance Sheets, Exchange Rates, Other, Stock Markets and Non-Household Balance Sheets. The macroeconomic series were transformed using the codes provided by McCracken and Ng (2021) to achieve stationarity. The data transformations for each macroeconomic series (MS) are: (1) no transformation; (2) $\Delta(MS_t)$; (3) $\Delta^2(MS_t)$; (4) $log(MS_t)$; (5) $\Delta log(MS_t)$; (6) $\Delta^2 log(MS_t)$; (7) $\Delta\left(\frac{MS_t}{MS_{t-1}} - 1.0\right)$.

Using these two sources of information and after carrying out preprocessing and data cleaning, a single analysis period was consolidated from 2002Q2 to 2020Q4, consisting of 75 observations over time and per bank, in the case of ROE and ROA. In the case of EBITDA margin, the period 2001 to 2020 is covered, equivalent to 20 observations over time per bank. Table 1 shows summary statistics of profitability according to the bank's market capitalization. The table shows time averages of the cross-sectional mean, standard deviation, medians, skewness, and kurtosis. The size of the bank influences the different statistics; for instance, the larger the bank is, the larger the profitability. On their side, the variance is very similar for the three groups of banks, although the annual measures present a greater standard deviation. EBITDA presents a larger negative skewness and greater kurtosis than the quarterly indicators. Table 1 summary statistics indicate that although the three indicators of profitability are similar, they also seem to convey different information, thus emphasizing the convenience of considering the three of them in our calculations.

5. Results

In 5.1, we present the estimated factors of banking profitability and three factors of economic activity and prices for the US economy. In section 5.2, we estimate the marginal R-squared of the regression of each banking profitability factor on each of the series conforming to the big data macroeconomic set, aiming to gain interpretability. Finally, in section 5.3, we present the factor loads, and we rank financial institutions according to their exposure (either negative or positive) to the three sources of profitability dynamics.

5.1. Banking profitability and macroeconomic factors

We use the codes provided by the author of the original methodology, S. Ng[5], on her website to estimate the optimal number of factors. Once we determine the number of factors, we follow the approach proposed by Josse and Husson (2012) and describe the methodology used to estimate such factors.

Table 2 shows the percentage of the total variance in the panel of each of our three profitability indicators, ROE, ROA, EBITDA, explained by the three estimated banking profitability factors. In the table, small, medium and large banks correspond to those below the 33rd percentile, between the 33rd and 66th percentiles, and above the 66th percentile of market capitalization, respectively. The table also includes the sample size, N, used in each case, alongside the sampling frequency, which can be either quarterly, Q, or yearly, Y. In Table 2, we observe a high percentage of the total system variation explained by the three factors selected in the first step, namely, between 63% and 68% for the three profitability indicators. This result is robust to using ROE, ROA and even EBITDA margin (N = 241), which is sampled at a different frequency and consists of a cross-sectional sample size that more than doubles that of ROE (N = 111) and ROA (N = 118). It is also robust to conditioning the results on the size of banks. Nevertheless, the percentage of explained variance increases for large banks with respect to small banks. The fact that the three factors explain similar percentages of the total

[5] https://www.columbia.edu/~sn2294/.

variance for ROE and ROA, rather than for EBIDTA, confirms our number of selected factors. In short, it means that there are three main forces underling the profitability dynamics in the banking industry and that large banks are more susceptible to profitability commonality than small banks.

In the Appendix, we compare the results presented in Table 2 with alternatives in the literature to estimate the factors, such as the NIPALS algorithm (Andrecut, 2009; Wold, 1966), classic PCA (Mardia et al., 1979), and factor-based imputation for missing data (Bai & Ng, 2019, 2021; Cahan et al., 2021), and we further confirm the robustness of our claims.

In what follows, to ease the exposition and given the similarities of the results for our three profitability indicators, we focus the exposition on ROE, while the results regarding ROA and EBITDA can be found in the Appendix. Fig. 2 shows the three banking factors for the total sample (solid line) and divides them according to bank size (dotted lines). Factor 1 presents a clear contraction in the wake of the Global Financial Crisis (GFC) in 2008–2009 and during the COVID-19 crisis in the first quarters of 2020. Factor 2 depicts smoother dynamics than factor 1, and it is depressed during the GFC. Factor 3 seems to recover from the crisis episodes around the GFC sooner than the other two factors. The three factors constructed with subsamples of small, medium and large banks present dynamics similar to those of the general factors, while the most noticeable divergence occurs during crisis episodes. In the case of ROA, Fig. 3 shows that factor 1 has a downward trend long before the subprime crisis. Indeed, after 2005, the contraction becomes more pronounced. After the crisis, it presents a rapid recovery until reaching a maximum in 2019, and it suffers a great contraction again in the wake of COVID-19. In the case of factors 2 and 3, a sharp fall is evidenced in 2008, and then a gradual recovery is registered. These factors are far less sensitive to the COVID-19 crisis. The dynamics of the profitability factors, conditioning on bank size, are similar across categories.

The ROE indicator is obtained by dividing a bank's net profit by its total equity. ROE is the most widely used indicator to assess the profitability of a bank. The higher the ROE is, the greater the profitability that the bank can generate with the equity it uses to finance its operations. A measure greater than 10% is usually considered strong (Koch & MacDonald, 2015). On its side, ROA divides the profitability of the bank using total assets instead as the ratio denominator. A measure greater than 1% is considered strong (Koch & MacDonald, 2015). Differences observed in practice between the time evolution of ROA and ROE and, hence, between the estimated factors show that a shock to profitability affects the capital structure of a bank. In general, from Figs. 2 and 3, we can observe that the dynamics of the estimated factors are very similar using either of the two indicators.

For the EBITDA margin, Fig. 4 shows that factor 1 presents a large contraction during the GFC (2008–2009) and the COVID-19 crisis. This behaviour is similar to the dynamics reported with respect to ROE and ROA. Regarding factors 2 and 3, there is a slight contraction after the GFC. If we focus our analysis on the small and mid-sized banks in factor 2, we note that the dynamics are the opposite; here, the small and medium banks show a contraction during the crisis and subsequently recover. Regarding factor 3, if we analyse the medium-sized banks, we note that they present a contraction during the crisis and subsequent recovery, this behaviour is the opposite of that for factor 3.

Fig. 5 shows three macroeconomic factors estimated from the FRED-QD database. As expected, extreme movements characterize the dynamics of the three macrofactors during crisis episodes, such as the GFC and the COVID-19 crisis. Interestingly, the factor's reaction to such episodes seems to occur before the depression recorded in banking factors 1 and 2.

5.2. Factor interpretation

Now, we turn our attention to the interpretation of our banking and macroeconomic factors. To do so, we estimate numerous, and exhaustive, bivariate OLS regressions in which the left-hand-side variable is the factor and the right-hand-side variable is each of the 248 macroeconomic series in the FRED-QD data set. From each regression, we keep the R-squared and construct a ranking, by factor, for the explanatory series, according to the predictive power of each variable on each factor. We interpret a factor according to the series it seems to be most closely related with. Table 3 shows the top 5 macroeconomic variables displaying great fit for the case of ROE factors. The variables are presented alongside their description and the group to which they belong, according to McCracken and Ng (2021). Note that we estimate three static factors, but only one dynamic or primitive factor. This means that even though each static factor is orthogonal to each other, by construction, there still exists only one primitive factor that determines the whole system dynamics. This primitive factor is likely related to the general and abstract concept of "economic activity", which includes characteristics of employability, income, financial burden, or industrial capacity utilization, etc.

The results show that factor 1 of banking profitability measured by ROE is mainly related to the level of household indebtedness (i.e., real estate loans and total real revolving credit owned and securitized) and with series that proxy for economic activity, particularly for industry capacity utilization. This first factor allows us to analyse how household indebtedness and industrial capacity, both of which are related to economic activity, are associated with bank profitability. In particular, the first static factor emphasizes the importance of mortgages and households' consumption for bank profitability (see for instance Jappelli et al. (2013)). Factor 2 is associated with household income, mainly with employment and the net worth of households and other economic actors. It could be rationalized as a forward-looking factor, according to which optimism on the side of households about income prospects, which can result in greater indebtedness and even greater interest payments. Factor 3 is clearly associated with stress in financial markets.

Regarding the identification of factors by bank size, we find a very similar dynamic for all factors; nevertheless, some differences are noteworthy. In the case of small banks, factor 1 is identical to factor 1 global (using the whole sample); in factor 2, some differences are perceived with respect to global factor 2, since for small entities, it is more closely associated with a series of liabilities of the nonfinancial business sector. Factor 3 is associated with the series with the net worth of households and nonprofit organizations, which are not as important for global factor 3. On the side of medium banks in comparison with the global factors, factor 1 is identical to global factor 1. Factor 2 includes a series of liabilities of the nonfinancial business sector, which are not included in the global factor, and factor 3 is more closely associated with a series of nonrevolving credits on property. Regarding large banks compared to global factors, factor 1 is more closely associated with the series of nonfinancial noncorporate real assets of the business sector; Factor 2 is more closely related to the series of liabilities of the nonfinancial business sector, while factor 3 makes a large difference since it is mainly associated with aspects of housing prices. The identification of the factors by bank size is presented in the Appendix.

Table 4 shows the variables that best explain the macroeconomic factors estimated from the FRED-QD database. In this case, the first factor is associated with income and production, the second factor is associated with prices, and the third factor is associated with real nonfinancial and household assets.

Fig. 6 shows the correlation between the banking factors and the estimated macroeconomic factors. As expected, the correlation within factor groups (i.e., the profitability and macroeconomic sets) is zero because factors within groups are orthogonal by construction. On the other hand, we observe that the most correlated factors are household income (Banking 2) and financial conditions (Macro 3), with a negative correlation of -0.44.

5.3. Sensitivity of banks to profitability factors

In this subsection, we estimate individual models for each bank in the study sample using the dynamic factor model presented in Eq. (1). Fig. 7 shows the kernel of the probability distribution of the adjusted R-squared, $\boldsymbol{R}^2_{Adj}$, alongside summary statistics of the distribution. In this way, we can evaluate the individual adjustment of the banking profitability dynamic factor model in the cross-section of banks. According to Fig. 7, $\boldsymbol{R}^2_{Adj}$ **is** greater than 64% for more than half of the banks and above 77% for more than a quarter of the banks. This shows a high adjustment of the dynamic factor model for the panel of financial institutions. On average, there is an adjustment of 60%, and some banks present adjustments greater than 90%.[6]

In Fig. 8, we present the distribution of $\boldsymbol{\beta}_i$ for $i = 0, 1, 2, 3$, which corresponds to the intercepts $\boldsymbol{\beta}_0$ and the factor loads of our model. $\boldsymbol{\beta}_0$ shows an estimation of banking profitability, which is not time varying, that is, a fixed effect of banking profitability. $\boldsymbol{\beta}_0$ has a distribution concentrated at approximately 9.63%, with half of the sample between 8.14% and 11.03%. The right panel of the figure shows the distribution of $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$. Analysing such a distribution allows us to identify the banks that are more vulnerable to shocks to each of the estimated factors. In the case of $\boldsymbol{\beta}_1$, it measures a bank's sensitivity to household burden and capacity utilization; for $\boldsymbol{\beta}_2$, it constitutes a risk indicator associated with household income; and $\boldsymbol{\beta}_3$ represents an indicator of risk according to stress in financial markets. The exposure of each bank to each factor depends naturally on the business model and a bank's specialization and market target. Regarding $\boldsymbol{\beta}_1$, most banks present values greater than zero, between 0.26% and 0.63%. In the case of $\boldsymbol{\beta}_2$ and $\boldsymbol{\beta}_3$, there is greater variability, and approximately 50% of the banks present values greater than zero (see Table 5).

In Fig. 9, we present the ranking of banks according to our three profitability factors. The spiral figure shows the magnitude of the estimated $\boldsymbol{\beta}_i$, which corresponds to the risk exposure to each factor. In Table 6, we show a summary of the top 10 banks according to the risk exposure to each systemic factor (see Figs. 10–13 and Table 7).

Upper panel Table 6 shows the first 10 positions of the ranking with the highest $\boldsymbol{R}^2_{Adj}$ for $\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$. The lower panel shows the 10 lowest positions according to the same criterion. The highest explanatory power of the general profitability factors that we identify here is shown by Westamerica Bancorp, Webster Financial Corp, and Fulton Financial Corp. Indeed, Central Pacific Financial Corp is the most vulnerable institution to the first and second factors associated with household indebtedness, economic activity and household income, respectively, followed by Synovus Financial Corp. Regarding the third factor, stress in financial markets, Popular Inc., is the most vulnerable financial institution. The following banks are jointly vulnerable to common factors according to the three factors: First Busey Corp, Popular Inc. and Huntington Bancshares Inc. In contrast, the following banks are only vulnerable to a single factor: Old Second Bancorp Inc, Banner Corp, Republic Bancorp Inc, Bank Ozk, Hanmi Financial Corp, Citigroup Inc. and Webster Financial Corp (see Tables 8–11).

Focusing on the lower ranking, a lower β_0 is related to a greater vulnerability to the model common factors, such as Central Pacific Financial Corp, United Community Banks Inc., and Seacoast Banking Corporation of Florida. We note that the Central Pacific Financial Corp is vulnerable to factors one and two, but it is not vulnerable to factor three: stress in financial markets. The more countercyclical banks in the face of shocks to factors one and two are German American Bancorp Inc. and Westamerica Bancorp, respectively (see Tables 12–16).

The heterogeneity of our ranking results demonstrates the convenience of the integrated approach that we propose to monitor bank profitability. The information conveyed by each factor is different and offers a new risk management perspective (see Table 17–23).

6. Conclusion

Using a sample of profitability indicators for the largest US banks according to market capitalization, we estimate the number of statistical factors that underlie profitability dynamics over time for the banking industry. Three factors are enough to describe 63.40%, 68% and 67.50% of ROE, ROA and EBITDA, respectively. The numbers increase according to bank size, which indicates that, as expected, the larger the bank is, the more cyclically it behaves. This provides a precise answer to the question of to what extent bank profitability is a matter of exposure to cyclical market forces related to the macroeconomy instead of bank-specific characteristics.

[6] In the appendix, we show the ranking of the banks according to their goodness of fit, including the banks for which our model better explains profitability.

Furthermore, we conduct an intensive search in a big data set comprising 248 macroeconomic variables for production, employment, housing, inventories, money and credit, and stock markets, among other groups, which are representative of the whole economy. Our results indicate that these three statistical factors are mainly related to households' financial burden and economic activity, households' income and employment and, in some cases, financial stress (for ROA and ROE), while mortgage and housing markets are related in other cases (for EBITDA). Finally, we also provide a means to monitor profitability in the banking industry from an integrative perspective by establishing rankings of the financial institutions according to their exposure (either positive or negative) to the three market forces that we identify. The convenience of our approach is highlighted by a high adjustment of the factor models when explaining individual banks' profitability and the insights gained in terms of market monitoring after resorting to the integrative approach that we advance; i.e., while some banks are sensitive to specific banking factors, other banks are more sensitive to other market factors. Thus, ideally, we should keep track of the three factors simultaneously.

Our proposal is simple, yet intuitive and comprehensive; hence, it can be easily implemented by regulators and banking managers to keep track of market evolution and the most vulnerable financial institutions.

We focus on the largest 111–118 banks in the US system (241 for EBITDA) with more reliable information in our sample period. When we split the sample according to market capitalization, our three groups, namely, "large", "medium" and "small", are to be interpreted bearing in mind this caveat; hence, we do not truly consider the smallest financial institutions. Given that our results seem more relevant for large banks than for small banks, it could be that for banks outside of our sample, which are even smaller, the results lack the same validity. It would be interesting for future studies to explore this avenue by increasing the sample coverage.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Orlando Joaqui-Barandica: Methodology, Software, Data curation, Writing – original draft, Visualization. **Diego F. Manotas-Duque:** Conceptualization, Investigation, Supervision. **Jorge M. Uribe:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

We thank IFABS 2021 Oxford Conference and the anonymous referees' the scientific committee for their useful suggestions.

Appendix

A.1. Multivariate analysis methodologies for factor estimation.
A.2. Complementary ROE results.
A.3. ROA results.
A.4. EBITDA results.

A.1. Multivariate analysis methodologies for factor estimation.

Method: PCA classic (NA = 0)

By the spectral decomposition theorem, the covariance matrix $\boldsymbol{S}$ may be written in the form.

$$\boldsymbol{S} = \boldsymbol{GLG}'$$

where $\boldsymbol{G}$, is an orthogonal matrix and $\boldsymbol{L}$ is a diagonal matrix of the eigenvalues of $\boldsymbol{S}$, $l_1 \geq l_2 \geq \cdots \geq l_p \geq 0$. The principal component transformation is defined by the rotation.

$$\boldsymbol{w}_r = \boldsymbol{G}'(\boldsymbol{x}_r - \overline{\boldsymbol{x}}), r = 1, \cdots, n.$$

Since $\boldsymbol{S}_w = \boldsymbol{G}'\boldsymbol{SG} = \boldsymbol{L}$ is diagonal, the columns of $\boldsymbol{W}$, called principal components, represent uncorrelated linear combinations of the variables. In the practice one hopes to summarize most of the variability in the data using only the principal components with the highest variances, thus reducing dimension. Under this method, the missing values were replaced by zeros.

Method: NIPALS algorithm

In the first step, the initial data X is copied into the residual matrix R. Then, in the next steps the algorithm extracts iteratively one component at a time ($k = 0, 1, \cdots, K \leq N$) by repeated regressions of $\boldsymbol{X}^T$ on scores $\boldsymbol{T}^{(k)}$ to obtain improved loads $\boldsymbol{P}^{(k)}$, and of $\boldsymbol{X}$ on these $\boldsymbol{P}^{(k)}$ to obtain improved scores $\boldsymbol{T}^{(k)}$. After the convergence is achieved, this process is following by a deflation of the data matrix:

$$\boldsymbol{X} \leftarrow \boldsymbol{X} - \boldsymbol{T}^{(k)} \left(\boldsymbol{P}^{(k)}\right)^T$$

The convergence test consists in comparing two successive estimates of the eigenvalue λ and $\lambda^{'}$. If the absolute difference $|\lambda - \lambda^{'}|$ is smaller than some small error ε then the convergence is achieved and the algorithm proceeds to the deflation step. Using the NIPALS-PCA algorithm approach, the decomposition of the data matrix **X** takes the form:

$$\boldsymbol{X} = \boldsymbol{T}_{(K)} \boldsymbol{P}_{(K)}^T + \boldsymbol{R},$$

where $\boldsymbol{T}_{(K)} = [\boldsymbol{T}^{(0)}|\ldots|\boldsymbol{T}^{(k-1)}]$ is the matrix formed using the first K scores, $\boldsymbol{P}_{(K)} = [\boldsymbol{P}^{(0)}|\ldots|\boldsymbol{P}^{(k-1)}]$ is the matrix of the first K loadings, and **R** is the residual matrix. The pseudo-code of the NIPALS-PCA algorithm is given below:

```
R ← X
for(k = 0, ⋯, K −1) do
  {
  λ = 0
  T(k) ← R(k)
  for(j = 0, ⋯, J) do
    {
    P(k) ← R(T)T(k)
    P(k) ← P(k)||P(k)||^−1
    T(k) ← RP(k)
    λ' ← ||T(k)||
    if(|λ' − λ| ≤ ε) then break
    λ ← λ'
    }
  R ← R −T(k)(P(k))^T
  }
return T, P, R
```

Method: Factor-Based Imputation for Missing Data

Let X be a $T \times N$ panel of data, $X_i = (X_{i1}, \cdots, X_{iT})^{'}$ be a $T \times 1$ vector of random variables and $X = (X_1, \cdots, X_N)$ be a $T \times N$ matrix. Let $i = 1, \cdots, N$ to index cross-section units and $t = 1, \cdots, T$ to index time series observations. In practice, X_i is transformed to be stationary, demeaned, and is often standardized. It is assumed that the normalized data $Z = \frac{X}{\sqrt{NT}}$ has singular value decomposition (SVD).

$$Z = \frac{X}{\sqrt{NT}} = UDV^{'} = U_r D_r V_r^{'} + U_{n-r} D_{n-r} V_{n-r}^{'}$$

where D_r is a diagonal matrix of r singular values ordered such that $d_1 \geq d_2 \geq \cdots \geq d_r$, while U_r, V_r are the corresponding left and right singular vectors respectively. It is assumed that the data X admit a strong factor a structure:

$$X = F\Lambda^{'} + e$$

where F is a $T \times r$ matrix of common factors, Λ is a $N \times r$ matrix of factor loadings, and e is a $T \times N$ matrix of idiosyncratic errors e. We estimate the factors and loadings by the method of static asymptotic principal components (APC).

A.2. Complementary ROE results

Table 8
FRED's top 5 macroeconomic variables that best explain the estimated banking factors with respect to ROE by market size.

Banking Factors	Group	Description	R^2_{Adj}
Small			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.69
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.45
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.43
	Industrial Production	Capacity Utilization: Total Industry (Percent of Capacity)	0.37
	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.27
Factor 2	Employment and Unemployment	Help-Wanted Index	0.60
	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.58
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.37
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.24
	Non-Household Balance Sheets	Nonfinancial Corporate Business Sector Liabilities to Disposable Business Income (Percent)	0.23
Factor 3	Non-Household Balance Sheets	Nonfinancial Noncorporate Business Sector Liabilities to Disposable Business Income (Percent)	0.29
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.26
	Money and Credit	FRB Senior Loans Officer Opions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans	0.25
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.25
	Money and Credit	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.22
Medium			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.67
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.51
	Industrial Production	Capacity Utilization: Total Industry (Percent of Capacity)	0.44
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.42
	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.36
Factor 2	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.57
	Employment and Unemployment	Help-Wanted Index	0.54
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.26
	Employment and Unemployment	All Employees: Financial Activities (Thousands of Persons)	0.22
	Non-Household Balance Sheets	Nonfinancial Corporate Business Sector Liabilities to Disposable Business Income (Percent)	0.19

(*continued on next page*)

Table 8 (*continued*)

Banking Factors	Group	Description	R^2_{Adj}
Factor 3	Money and Credit	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.24
	Non-Household Balance Sheets	Nonfinancial Noncorporate Business Sector Liabilities to Disposable Business Income (Percent)	0.20
	Money and Credit	FRB Senior Loans Officer Opions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans	0.20
	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.20
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.19
Large			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.58
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.57
	Industrial Production	Capacity Utilization: Total Industry (Percent of Capacity)	0.49
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.39
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Assets (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.37
Factor 2	Employment and Unemployment	Help-Wanted Index	0.60
	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.59
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.38
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.21
	Non-Household Balance Sheets	Nonfinancial Corporate Business Sector Liabilities to Disposable Business Income (Percent)	0.20
Factor 3	Housing	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)	0.26
	Housing	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)	0.24
	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.19
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.18
	Interest Rates	3-Month Commercial Paper Minus Federal Funds Rate	0.12

Note: This table presents the macroeconomic series of the FRED-QD most correlated according to the R^2_{Adj} criterion with each of the banking factors estimated from ROE. Each of the series is classified into a group determined by Stock and Watson (2012). The results are grouped into sections of small, medium, and large banks according to their market capitalization.

Table 9
Top 10 small banks according to the estimated parameters of the model by factors using ROE.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Sierra Bancorp	0.883	City Holding Co	15.56	Central Pacific Financial Corp	4.44	Central Pacific Financial Corp	7.09	Republic Bancorp Inc	3.43
2	American River Bankshares	0.857	Stock Yards Bancorp Inc	15.24	First Busey Corp	2.62	First Busey Corp	3.27	First Busey Corp	2.53
3	1st Constitution Bancorp	0.815	Southside Bancshares Inc	13.73	Old Second Bancorp Inc	2.43	Old Second Bancorp Inc	2.43	Hanmi Financial Corp	2.38
4	Washington Trust Bancorp Inc	0.730	Great Southern Bancorp Inc	13.58	Heritage Commerce Corp	1.59	Heritage Commerce Corp	2.33	Financial Institutions Inc	1.55
5	Stock Yards Bancorp Inc	0.721	Republic Bancorp Inc	12.97	Republic First Bancorp Inc	1.49	Financial Institutions Inc	2.22	Lakeland Bancorp Inc	0.88
6	Capital City Bank Group Inc	0.715	Tompkins Financial Corp	12.86	First Community Bankshares Inc	1.38	Hanmi Financial Corp	2.06	City Holding Co	0.86
7	Lakeland Bancorp Inc	0.706	Washington Trust Bancorp Inc	12.65	Hanmi Financial Corp	1.24	Mercantile Bank Corp	1.79	Boston Private Financial Holdings Inc	0.78
8	Bank of Marin Bancorp	0.696	Sierra Bancorp	12.50	Sierra Bancorp	1.22	Boston Private Financial Holdings Inc	1.24	Great Southern Bancorp Inc	0.64
9	Great Southern Bancorp Inc	0.684	Bank of Marin Bancorp	11.87	Mercantile Bank Corp	1.13	Brookline Bancorp Inc	0.99	Bank of Marin Bancorp	0.61
10	Mercantile Bank Corp	0.675	Horizon Bancorp Inc	11.55	Great Southern Bancorp Inc	1.07	Berkshire Hills Bancorp Inc	0.82	Southside Bancshares Inc	0.60
Lower ranking of banks										
1	Bryn Mawr Bank Corp	0.099	Central Pacific Financial Corp	0.75	German American Bancorp Inc	−0.43	Republic Bancorp Inc	−1.72	Old Second Bancorp Inc	−9.92
2	Berkshire Hills Bancorp Inc	0.199	Republic First Bancorp Inc	3.67	Brookline Bancorp Inc	−0.13	Southside Bancshares Inc	−1.42	Central Pacific Financial Corp	−3.49
3	Heritage Commerce Corp	0.210	Old Second Bancorp Inc	3.74	Southside Bancshares Inc	−0.10	Sierra Bancorp	−1.07	Republic First Bancorp Inc	−1.97
4	First Financial Corp	0.293	Berkshire Hills Bancorp Inc	5.45	Republic Bancorp Inc	0.10	American River Bankshares	−0.82	Heritage Commerce Corp	−1.70
5	Republic Bancorp Inc	0.298	Brookline Bancorp Inc	5.57	First Financial Corp	0.16	Bank of Marin Bancorp	−0.71	Sierra Bancorp	−1.18
6	Tompkins Financial Corp	0.323	Heritage Commerce Corp	5.79	Berkshire Hills Bancorp Inc	0.28	S&T Bancorp Inc	−0.42	Capital City Bank Group Inc	−0.99
7	Community Trust Bancorp Inc	0.355	Capital City Bank Group Inc	5.93	Bryn Mawr Bank Corp	0.31	Tompkins Financial Corp	−0.37	American River Bankshares	−0.87
8	Central Pacific Financial Corp	0.407	Mercantile Bank Corp	6.86	Tompkins Financial Corp	0.31	City Holding Co	−0.34	S&T Bancorp Inc	−0.60
9	Northrim BanCorp Inc	0.410	Financial Institutions Inc	7.38	Community Trust Bancorp Inc	0.39	American National Bankshares Inc	−0.33	Heritage Financial Corp	−0.58
10	First Community Bankshares Inc	0.417	First Busey Corp	7.50	Stock Yards Bancorp Inc	0.45	Republic First Bancorp Inc	−0.30	First Commonwealth Financial Corp	−0.51

Note: This table presents the consolidation of the top 10 small banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 10
Top 10 medium banks according to the estimated parameters of the model by factors using ROE.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Westamerica Bancorp	0.887	Bank of Hawaii Corp	18.09	United Community Banks Inc	2.93	United Community Banks Inc	4.21	Pacific Premier Bancorp Inc	1.75
2	Trustmark Corp	0.885	Westamerica Bancorp	17.72	Seacoast Banking Corporation of Florida	2.57	Seacoast Banking Corporation of Florida	3.49	OceanFirst Financial Corp	1.56
3	Hope Bancorp Inc	0.876	CVB Financial Corp	13.50	Hope Bancorp Inc	1.40	Banner Corp	2.48	Seacoast Banking Corporation of Florida	0.66
4	Cathay General Bancorp	0.871	Lakeland Financial Corp	13.20	First Midwest Bancorp Inc	1.31	Ameris Bancorp	1.67	Community Bank System Inc	0.59
5	Atlantic Union Bankshares Corp	0.855	Park National Corp	12.66	Associated Banc-Corp	1.29	Eagle Bancorp Inc	1.06	Heartland Financial USA Inc	0.52
6	NBT Bancorp Inc	0.847	NBT Bancorp Inc	11.70	Banner Corp	1.24	First Merchants Corp	1.02	Park National Corp	0.52
7	Columbia Banking System Inc	0.838	BancFirst Corp	11.62	Sandy Spring Bancorp Inc	1.04	Heartland Financial USA Inc	0.72	Sandy Spring Bancorp Inc	0.51
8	Fulton Financial Corp	0.832	Eagle Bancorp Inc	11.12	Cathay General Bancorp	1.03	Cathay General Bancorp	0.69	Renasant Corp	0.44
9	CVB Financial Corp	0.828	Independent Bank Corp (Massachusetts)	11.05	Ameris Bancorp	0.99	Umpqua Holdings Corp	0.63	Trustmark Corp	0.37
10	Associated Banc-Corp	0.791	Hope Bancorp Inc	10.93	Westamerica Bancorp	0.98	Pacific Premier Bancorp Inc	0.52	Fulton Financial Corp	0.37
Lower ranking of banks										
1	First Financial Bancorp	0.192	United Community Banks Inc	2.26	Eagle Bancorp Inc	0.15	Westamerica Bancorp	−2.36	United Community Banks Inc	−10.05
2	Pacific Premier Bancorp Inc	0.239	Seacoast Banking Corporation of Florida	3.41	Community Bank System Inc	0.18	Bank of Hawaii Corp	−1.18	Bank of Hawaii Corp	−1.31
3	Simmons First National Corp	0.416	Banner Corp	4.44	First Financial Bancorp	0.21	CVB Financial Corp	−0.88	Hancock Whitney Corp	−1.11
4	BancFirst Corp	0.422	Umpqua Holdings Corp	6.93	Simmons First National Corp	0.26	Hancock Whitney Corp	−0.87	Banner Corp	−1.05
5	OceanFirst Financial Corp	0.454	First Merchants Corp	7.77	OceanFirst Financial Corp	0.27	NBT Bancorp Inc	−0.75	BancorpSouth Bank	−0.95
6	Bank of Hawaii Corp	0.461	Ameris Bancorp	7.85	BancFirst Corp	0.36	F.N.B. Corp	−0.68	Trico Bancshares	−0.92
7	Old National Bancorp	0.505	Renasant Corp	8.17	Bank of Hawaii Corp	0.37	OceanFirst Financial Corp	−0.64	First Midwest Bancorp Inc	−0.68
8	Hancock Whitney Corp	0.511	WesBanco Inc	8.21	Lakeland Financial Corp	0.40	Trustmark Corp	−0.58	BancFirst Corp	−0.57
9	Lakeland Financial Corp	0.567	Columbia Banking System Inc	8.39	NBT Bancorp Inc	0.43	First Midwest Bancorp Inc	−0.36	Ameris Bancorp	−0.56
10	Heartland Financial USA Inc	0.582	Associated Banc-Corp	8.66	WesBanco Inc	0.44	BancorpSouth Bank	−0.33	Simmons First National Corp	−0.26

Note: This table presents the consolidation of the top 10 medium banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 11
Top 10 large banks according to the estimated parameters of the model by factors using ROE.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	East West Bancorp Inc	0.874	Bank Ozk	16.99	Synovus Financial Corp	3.40	Synovus Financial Corp	3.03	PacWest Bancorp	1.44
2	Zions Bancorporation NA	0.873	U.S. Bancorp	16.13	Popular Inc	2.60	Huntington Bancshares Inc	2.87	SVB Financial Group	1.31
3	Webster Financial Corp	0.868	First Financial Bankshares Inc	14.22	Huntington Bancshares Inc	2.57	Popular Inc	2.11	Texas Capital Bancshares Inc	1.19
4	Cullen/Frost Bankers Inc	0.863	Wells Fargo & Co	13.06	Regions Financial Corp	2.08	Regions Financial Corp	2.00	Comerica Inc	1.05
5	Regions Financial Corp	0.837	Commerce Bancshares Inc	12.90	First Horizon Corp (Tennessee)	1.99	Zions Bancorporation NA	1.28	U.S. Bancorp	0.90
6	United Bankshares Inc	0.826	Cullen/Frost Bankers Inc	12.74	Zions Bancorporation NA	1.91	East West Bancorp Inc	1.24	UMB Financial Corp	0.85
7	Valley National Bancorp	0.826	SVB Financial Group	12.70	Citigroup Inc	1.78	Webster Financial Corp	1.18	Commerce Bancshares Inc	0.55
8	KeyCorp	0.824	Valley National Bancorp	12.09	KeyCorp	1.58	SVB Financial Group	1.16	United Bankshares Inc	0.50
9	Truist Financial Corp	0.824	East West Bancorp Inc	11.67	Fifth Third Bancorp	1.49	KeyCorp	1.10	M&T Bank Corp	0.50
10	Comerica Inc	0.803	Glacier Bancorp Inc	11.59	Webster Financial Corp	1.36	Pinnacle Financial Partners Inc	0.92	Synovus Financial Corp	0.49
Lower ranking of banks										
1	South State Corp	0.144	Synovus Financial Corp	3.89	UMB Financial Corp	−0.17	Valley National Bancorp	−1.74	Popular Inc	−2.52
2	People's United Financial Inc	0.233	Regions Financial Corp	5.35	First Financial Bankshares Inc	0.15	Bank Ozk	−1.39	First Horizon Corp (Tennessee)	−2.46
3	Bank Ozk	0.269	Popular Inc	5.68	South State Corp	0.33	United Bankshares Inc	−1.18	Citigroup Inc	−1.40
4	JPMorgan Chase & Co	0.436	Zions Bancorporation NA	5.94	Prosperity Bancshares Inc	0.38	Bank of America Corp	−0.96	South State Corp	−1.12
5	M&T Bank Corp	0.437	People's United Financial Inc	6.37	PacWest Bancorp	0.38	Cullen/Frost Bankers Inc	−0.87	Regions Financial Corp	−0.90
6	Pinnacle Financial Partners Inc	0.500	Pinnacle Financial Partners Inc	6.81	JPMorgan Chase & Co	0.41	U.S. Bancorp	−0.85	East West Bancorp Inc	−0.87
7	UMB Financial Corp	0.505	Huntington Bancshares Inc	7.41	Texas Capital Bancshares Inc	0.42	South State Corp	−0.77	Huntington Bancshares Inc	−0.86
8	Texas Capital Bancshares Inc	0.514	PacWest Bancorp	7.50	BOK Financial Corp	0.43	Prosperity Bancshares Inc	−0.69	People's United Financial Inc	−0.78
9	Glacier Bancorp Inc	0.530	Webster Financial Corp	7.97	M&T Bank Corp	0.44	Wells Fargo & Co	−0.65	Prosperity Bancshares Inc	−0.75
10	PacWest Bancorp	0.540	UMB Financial Corp	8.01	United Bankshares Inc	0.44	Truist Financial Corp	−0.63	Webster Financial Corp	−0.75

Note: This table presents the consolidation of the top 10 large banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

A.3. ROA results

Table 12
Top 5 of FRED's macroeconomic variables that best explain banking factors using ROA.

Banking Factors	Group	Description	R^2_{Adj}
All			
Factor 1	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.40
	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.37
	Housing	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)	0.34
	Housing	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)	0.33
	NIPA	Real private fixed investment: Residential (Billions of Chained 2012 Dollars), deflated using PCE	0.33
Factor 2	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.48
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.45
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.44
	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.27
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.26
Factor 3	Employment and Unemployment	Help-Wanted Index	0.44
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.41
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.34
	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.34
	Interest Rates	5-Year Treasury Constant Maturity Minus Federal Funds Rate	0.31

Note: This table presents the macroeconomic series of the FRED-QD most correlated with each of the banking factors estimated according to the R^2_{Adj} criterion. Each of the series is classified into a group determined by Stock and Watson (2012).

Table 13
FRED's top 5 macroeconomic variables that best explain the estimated banking factors with respect to ROA by market size.

Banking Factors	Group	Description	R^2_{Adj}
Small			
Factor 1	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.39
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.36
	Housing	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)	0.33
	NIPA	Real private fixed investment: Residential (Billions of Chained 2012 Dollars), deflated using PCE	0.33
	Housing	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)	0.33
Factor 2	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.60
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.49
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.28
	Household Balance Sheets	Liabilities of Households and Nonprofit Organizations Relative to Personal Disposable Income (Percent)	0.23
	Other	University of Michigan: Consumer Sentiment (Index 1st Quarter 1966 = 100)	0.20
Factor 3	Employment and Unemployment	Help-Wanted Index	0.36
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.32
	Interest Rates	5-Year Treasury Constant Maturity Minus Federal Funds Rate	0.28
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.26
	Interest Rates	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	0.21

(*continued on next page*)

Table 13 (*continued*)

Banking Factors	Group	Description	R^2_{Adj}
Medium			
Factor 1	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.42
	Other	University of Michigan: Consumer Sentiment (Index 1st Quarter 1966 = 100)	0.34
	Housing	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)	0.33
	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.33
	Housing	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)	0.32
Factor 2	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.41
	Interest Rates	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill, secondary market (Percent)	0.37
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.36
	Interest Rates	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	0.35
	Interest Rates	5-Year Treasury Constant Maturity Minus Federal Funds Rate	0.28
Factor 3	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.15
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.13
	Employment and Unemployment	Help-Wanted Index	0.12
	Household Balance Sheets	Liabilities of Households and Nonprofit Organizations Relative to Personal Disposable Income (Percent)	0.10
	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.10
Large			
Factor 1	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.40
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.39
	Housing	S&P/Case-Shiller 20-City Composite Home Price Index (Index January 2000 = 100)	0.34
	NIPA	Real private fixed investment: Residential (Billions of Chained 2012 Dollars), deflated using PCE	0.34
	Housing	S&P/Case-Shiller 10-City Composite Home Price Index (Index January 2000 = 100)	0.33
Factor 2	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.51
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.44
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.38
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.25
	Interest Rates	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	0.24
Factor 3	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.30
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.26
	Employment and Unemployment	Help-Wanted Index	0.23
	Earnings and Productivity	Manufacturing Sector: Real Output Per Hour of All Persons (Index 2012 = 100)	0.19
	Interest Rates	5-Year Treasury Constant Maturity Minus Federal Funds Rate	0.17

Note: This table presents the macroeconomic series of the FRED-QD most correlated according to the R^2_{Adj} criterion with each of the banking factors estimated from ROA. Each of the series is classified into a group determined by Stock and Watson (2012). The results are grouped into sections of small, medium, and large banks according to their market capitalization.

Table 14
Top 10 banks according to the estimated parameters of the model by factors using ROA.

Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3	Bank
Top ranking of banks										
1	Cathay General Bancorp	0.943	Bank Ozk	1.52	CVB Financial Corp	0.11	Central Pacific Financial Corp	0.39	Central Pacific Financial Corp	0.22
2	TCF Financial Corp	0.924	First Financial Bankshares Inc	1.45	Central Pacific Financial Corp	0.10	United Community Banks Inc	0.37	United Community Banks Inc	0.19
3	Washington Trust Bancorp Inc	0.918	Sierra Bancorp	1.41	First Busey Corp	0.09	Synovus Financial Corp	0.27	Heritage Commerce Corp	0.18
4	NBT Bancorp Inc	0.913	CVB Financial Corp	1.40	Synovus Financial Corp	0.08	Seacoast Banking Corporation of Florida	0.24	Banner Corp	0.14
5	German American Bancorp Inc	0.910	Westamerica Bancorp	1.32	Huntington Bancshares Inc	0.08	Sierra Bancorp	0.23	Pinnacle Financial Partners Inc	0.14
6	First Financial Bankshares Inc	0.905	City Holding Co	1.30	Seacoast Banking Corporation of Florida	0.08	Heritage Commerce Corp	0.22	Enterprise Financial Services Corp	0.13
7	WesBanco Inc	0.901	Stock Yards Bancorp Inc	1.17	East West Bancorp Inc	0.07	Associated Banc-Corp	0.13	Eagle Bancorp Inc	0.13
8	Lakeland Financial Corp	0.900	U.S. Bancorp	1.17	Community Trust Bancorp Inc	0.07	Old Second Bancorp Inc	0.12	Seacoast Banking Corporation of Florida	0.13
9	JPMorgan Chase & Co	0.878	Republic Bancorp Inc	1.17	First Community Bankshares Inc	0.07	Republic First Bancorp Inc	0.12	German American Bancorp Inc	0.12
10	Prosperity Bancshares Inc	0.875	Community Trust Bancorp Inc	1.16	Cathay General Bancorp	0.07	First Community Bankshares Inc	0.11	PacWest Bancorp	0.11
Lower ranking of banks										
1	Sierra Bancorp	−0.013	Republic First Bancorp Inc	0.17	Sierra Bancorp	−0.02	Hanmi Financial Corp	−0.17	CVB Financial Corp	−0.30
2	Central Valley Community Bancorp	−0.011	Central Pacific Financial Corp	0.29	Central Valley Community Bancorp	0.01	Bank Ozk	−0.13	Westamerica Bancorp	−0.15
3	BancFirst Corp	0.033	Seacoast Banking Corporation of Florida	0.35	Republic First Bancorp Inc	0.02	Republic Bancorp Inc	−0.11	BancFirst Corp	−0.13
4	Old Second Bancorp Inc	0.101	United Community Banks Inc	0.36	Bancorp Inc	0.02	German American Bancorp Inc	−0.08	Community Trust Bancorp Inc	−0.12
5	Bancorp Inc	0.136	Bancorp Inc	0.38	First of Long Island Corp	0.02	Southside Bancshares Inc	−0.08	S&T Bancorp Inc	−0.11
6	Republic Bancorp Inc	0.145	Capital City Bank Group Inc	0.42	Capital City Bank Group Inc	0.03	First of Long Island Corp	−0.07	Valley National Bancorp	−0.09
7	Community Trust Bancorp Inc	0.154	Heritage Commerce Corp	0.43	UMB Financial Corp	0.03	First Financial Bankshares Inc	−0.06	Sierra Bancorp	−0.07
8	Heritage Commerce Corp	0.186	Banner Corp	0.48	People's United Financial Inc	0.03	Horizon Bancorp Inc	−0.06	American National Bankshares Inc	−0.07
9	CVB Financial Corp	0.189	Synovus Financial Corp	0.53	Flushing Financial Corp	0.03	Signature Bank	−0.06	First Horizon Corp (Tennessee)	−0.07
10	Hanmi Financial Corp	0.192	First Community Corp (South Carolina)	0.54	American River Bankshares	0.03	Eagle Bancorp Inc	−0.06	Bank of Hawaii Corp	−0.06

Note: This table presents the consolidation of the top 10 banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 15
Top 10 small banks according to the estimated parameters of the model by factors using ROA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Washington Trust Bancorp Inc	0.921	Sierra Bancorp	1.39	Community Trust Bancorp Inc	0.15	Central Pacific Financial Corp	0.52	Central Pacific Financial Corp	0.71
2	Lakeland Bancorp Inc	0.881	Hanmi Financial Corp	1.38	Central Pacific Financial Corp	0.14	Sierra Bancorp	0.31	Heritage Commerce Corp	0.33
3	Horizon Bancorp Inc	0.871	City Holding Co	1.30	Old Second Bancorp Inc	0.13	Heritage Commerce Corp	0.31	First Community Bankshares Inc	0.26
4	First of Long Island Corp	0.870	Stock Yards Bancorp Inc	1.18	West Bancorporation Inc	0.12	Old Second Bancorp Inc	0.25	Old Second Bancorp Inc	0.25
5	German American Bancorp Inc	0.855	Republic Bancorp Inc	1.16	First Community Bankshares Inc	0.12	Central Valley Community Bancorp	0.22	Mercantile Bank Corp	0.17
6	Tompkins Financial Corp	0.850	Community Trust Bancorp Inc	1.16	City Holding Co	0.11	Community Trust Bancorp Inc	0.18	German American Bancorp Inc	0.11
7	Stock Yards Bancorp Inc	0.839	Central Valley Community Bancorp	1.07	Stock Yards Bancorp Inc	0.11	Republic First Bancorp Inc	0.16	Bryn Mawr Bank Corp	0.11
8	1st Constitution Bancorp	0.838	West Bancorporation Inc	1.04	S&T Bancorp Inc	0.10	First Bancorp (North Carolina)	0.13	Horizon Bancorp Inc	0.11
9	West Bancorporation Inc	0.823	S&T Bancorp Inc	1.01	Great Southern Bancorp Inc	0.10	Mercantile Bank Corp	0.13	Berkshire Hills Bancorp Inc	0.10
10	First Community Corp (South Carolina)	0.809	First Financial Corp	0.97	Boston Private Financial Holdings Inc	0.10	American River Bankshares	0.12	Capital City Bank Group Inc	0.08
Lower ranking of banks										
1	Sierra Bancorp	−0.016	Republic First Bancorp Inc	0.21	Sierra Bancorp	−0.07	Hanmi Financial Corp	−0.45	Hanmi Financial Corp	−0.65
2	Central Valley Community Bancorp	0.003	Central Pacific Financial Corp	0.29	Republic First Bancorp Inc	0.02	Republic Bancorp Inc	−0.19	Community Trust Bancorp Inc	−0.14
3	Old Second Bancorp Inc	0.150	Capital City Bank Group Inc	0.41	Central Valley Community Bancorp	0.03	German American Bancorp Inc	−0.14	S&T Bancorp Inc	−0.13
4	Heritage Commerce Corp	0.169	Heritage Commerce Corp	0.43	Capital City Bank Group Inc	0.05	First of Long Island Corp	−0.11	Republic First Bancorp Inc	−0.13
5	Republic Bancorp Inc	0.174	First Community Corp (South Carolina)	0.54	First of Long Island Corp	0.05	Horizon Bancorp Inc	−0.10	Republic Bancorp Inc	−0.09
6	Community Trust Bancorp Inc	0.215	Berkshire Hills Bancorp Inc	0.55	Berkshire Hills Bancorp Inc	0.06	Southside Bancshares Inc	−0.10	American National Bankshares Inc	−0.09
7	First Bancorp (North Carolina)	0.304	Mercantile Bank Corp	0.64	American River Bankshares	0.06	Bryn Mawr Bank Corp	−0.09	City Holding Co	−0.09
8	Republic First Bancorp Inc	0.393	American River Bankshares	0.66	Flushing Financial Corp	0.06	Financial Institutions Inc	−0.08	Boston Private Financial Holdings Inc	−0.08
9	Berkshire Hills Bancorp Inc	0.411	First Bancorp (North Carolina)	0.69	1st Constitution Bancorp	0.07	First Financial Corp	−0.06	Brookline Bancorp Inc	−0.06
10	First Community Bankshares Inc	0.449	Flushing Financial Corp	0.69	Southside Bancshares Inc	0.07	Washington Trust Bancorp Inc	−0.05	West Bancorporation Inc	−0.06

Note: This table presents the consolidation of the top 10 small banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 16
Top 10 medium banks according to the estimated parameters of the model by factors using ROA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	NBT Bancorp Inc	0.931	CVB Financial Corp	1.38	CVB Financial Corp	0.19	United Community Banks Inc	0.74	BancFirst Corp	0.94
2	Cathay General Bancorp	0.929	Westamerica Bancorp	1.33	First Busey Corp	0.15	Seacoast Banking Corporation of Florida	0.42	Westamerica Bancorp	0.33
3	WesBanco Inc	0.914	BancFirst Corp	1.19	United Community Banks Inc	0.14	Banner Corp	0.22	Associated Banc-Corp	0.19
4	Westamerica Bancorp	0.898	Park National Corp	1.04	Seacoast Banking Corporation of Florida	0.14	Ameris Bancorp	0.16	CVB Financial Corp	0.16
5	Umpqua Holdings Corp	0.870	Bank of Hawaii Corp	1.02	Cathay General Bancorp	0.12	Associated Banc-Corp	0.13	United Community Banks Inc	0.11
6	Atlantic Union Bankshares Corp	0.842	Lakeland Financial Corp	1.00	Ameris Bancorp	0.10	First Busey Corp	0.11	Park National Corp	0.10
7	Ameris Bancorp	0.838	Cathay General Bancorp	0.99	First Merchants Corp	0.10	First Merchants Corp	0.09	Seacoast Banking Corporation of Florida	0.09
8	First Merchants Corp	0.830	Eagle Bancorp Inc	0.97	Enterprise Financial Services Corp	0.10	Umpqua Holdings Corp	0.09	Hancock Whitney Corp	0.07
9	First Financial Bancorp	0.829	Hope Bancorp Inc	0.93	Sandy Spring Bancorp Inc	0.10	Cathay General Bancorp	0.08	First Busey Corp	0.06
10	Lakeland Financial Corp	0.822	Trustmark Corp	0.92	Umpqua Holdings Corp	0.10	First Midwest Bancorp Inc	0.07	Hope Bancorp Inc	0.06
Lower ranking of banks										
1	CVB Financial Corp	0.115	Seacoast Banking Corporation of Florida	0.34	Bancorp Inc	0.04	Westamerica Bancorp	−0.21	Eagle Bancorp Inc	−0.19
2	Bancorp Inc	0.167	United Community Banks Inc	0.35	Bank of Hawaii Corp	0.06	CVB Financial Corp	−0.14	Enterprise Financial Services Corp	−0.12
3	BancorpSouth Bank	0.339	Bancorp Inc	0.38	Hancock Whitney Corp	0.06	Bank of Hawaii Corp	−0.12	Lakeland Financial Corp	−0.12
4	Hancock Whitney Corp	0.405	Banner Corp	0.49	F.N.B. Corp	0.06	Trustmark Corp	−0.08	Simmons First National Corp	−0.09
5	First Busey Corp	0.414	First Busey Corp	0.60	BancorpSouth Bank	0.06	NBT Bancorp Inc	−0.08	Old National Bancorp	−0.08
6	United Community Banks Inc	0.464	Heartland Financial USA Inc	0.65	OceanFirst Financial Corp	0.07	OceanFirst Financial Corp	−0.08	Bancorp Inc	−0.05
7	BancFirst Corp	0.582	Ameris Bancorp	0.67	NBT Bancorp Inc	0.07	Hancock Whitney Corp	−0.08	First Commonwealth Financial Corp	−0.04
8	Banner Corp	0.596	Associated Banc-Corp	0.67	Simmons First National Corp	0.07	BancFirst Corp	−0.07	WesBanco Inc	−0.04
9	Old National Bancorp	0.598	First Midwest Bancorp Inc	0.67	Westamerica Bancorp	0.07	Fulton Financial Corp	−0.06	NBT Bancorp Inc	−0.04
10	First Midwest Bancorp Inc	0.613	First Commonwealth Financial Corp	0.68	BancFirst Corp	0.07	Simmons First National Corp	−0.06	Heartland Financial USA Inc	−0.03

Note: This table presents the consolidation of the top 10 medium banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

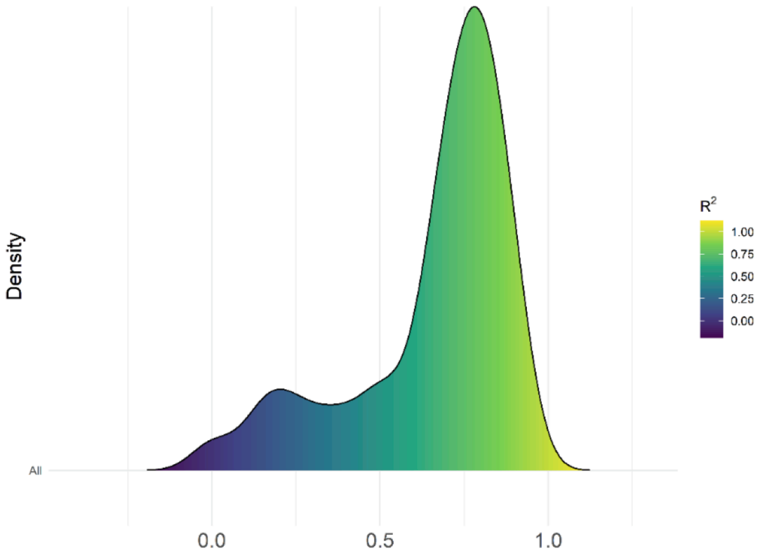

Fig. 10. Distribution of R^2 of the model by factors. **Note:** This figure shows the density about $\boldsymbol{R}^2_{Adj}$ for the set of regressions of the dynamic factor models from ROA.

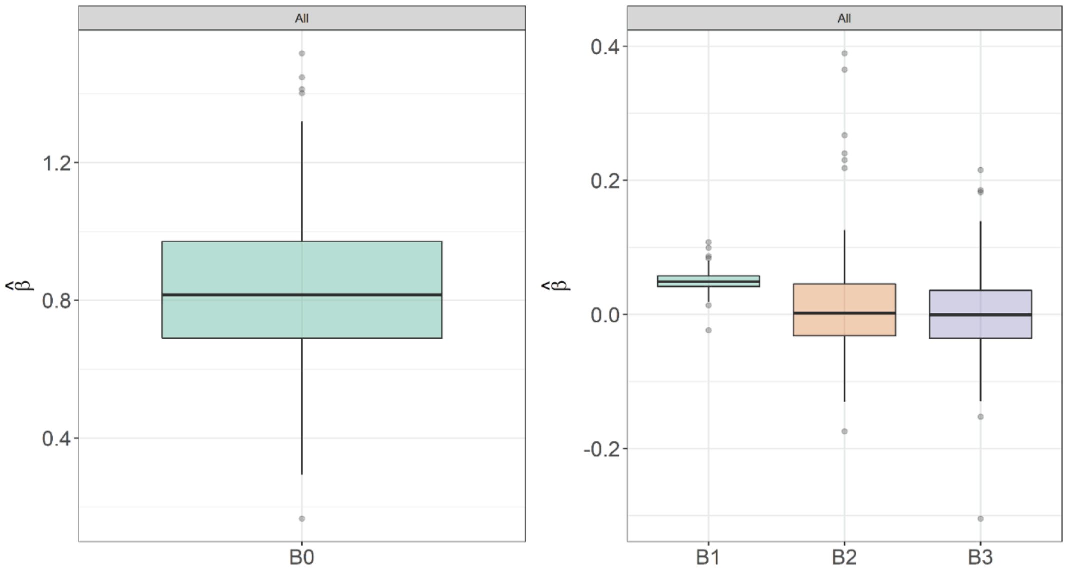

Fig. 11. Distribution of model estimators by factors from ROA. **Note:** The left panel shows the distribution of the $\boldsymbol{\beta}_0$ estimator that represents the fixed effect. The right panel shows the distribution of the estimates of the effect $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$ of the banking factors.

A.3. EBITDA results

Table 17
Top 10 large banks according to the estimated parameters of the model by factors using ROA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	First Financial Bankshares Inc	0.894	Bank Ozk	1.52	Huntington Bancshares Inc	0.13	Synovus Financial Corp	0.46	Pacific Premier Bancorp Inc	0.25
2	TCF Financial Corp	0.889	First Financial Bankshares Inc	1.45	Synovus Financial Corp	0.13	Regions Financial Corp	0.18	Pinnacle Financial Partners Inc	0.21
3	Valley National Bancorp	0.878	U.S. Bancorp	1.16	East West Bancorp Inc	0.12	Zions Bancorporation NA	0.17	PacWest Bancorp	0.20
4	Prosperity Bancshares Inc	0.877	Prosperity Bancshares Inc	1.14	Bank Ozk	0.12	Bank of America Corp	0.16	People's United Financial Inc	0.15
5	United Bankshares Inc	0.870	Commerce Bancshares Inc	1.07	Regions Financial Corp	0.12	Popular Inc	0.15	Signature Bank	0.10
6	Signature Bank	0.869	Wells Fargo & Co	1.03	First Horizon Corp (Tennessee)	0.11	First Horizon Corp (Tennessee)	0.14	Zions Bancorporation NA	0.09
7	Commerce Bancshares Inc	0.855	Glacier Bancorp Inc	1.03	KeyCorp	0.11	Comerica Inc	0.08	KeyCorp	0.07
8	Synovus Financial Corp	0.848	Truist Financial Corp	1.00	First Financial Bankshares Inc	0.11	Huntington Bancshares Inc	0.08	Regions Financial Corp	0.07
9	Zions Bancorporation NA	0.845	East West Bancorp Inc	1.00	Popular Inc	0.10	Pinnacle Financial Partners Inc	0.08	Popular Inc	0.07
10	Webster Financial Corp	0.828	PNC Financial Services Group Inc	1.00	Fifth Third Bancorp	0.10	PacWest Bancorp	0.08	Comerica Inc	0.06
Lower ranking of banks										
1	South State Corp	0.225	Synovus Financial Corp	0.54	UMB Financial Corp	0.05	Bank Ozk	−0.24	Valley National Bancorp	−0.19
2	Popular Inc	0.337	Zions Bancorporation NA	0.54	People's United Financial Inc	0.05	Signature Bank	−0.11	South State Corp	−0.12
3	People's United Financial Inc	0.443	Citigroup Inc	0.55	Valley National Bancorp	0.06	First Financial Bankshares Inc	−0.11	First Horizon Corp (Tennessee)	−0.12
4	Wells Fargo & Co	0.499	Bank of America Corp	0.59	JPMorgan Chase & Co	0.06	Prosperity Bancshares Inc	−0.10	Bank of America Corp	−0.12
5	Huntington Bancshares Inc	0.526	Regions Financial Corp	0.62	Wintrust Financial Corp	0.06	JPMorgan Chase & Co	−0.08	United Bankshares Inc	−0.09
6	Pacific Premier Bancorp Inc	0.584	UMB Financial Corp	0.64	Bank of America Corp	0.07	UMB Financial Corp	−0.07	Truist Financial Corp	−0.08
7	Citigroup Inc	0.603	Popular Inc	0.64	Cullen/Frost Bankers Inc	0.07	M&T Bank Corp	−0.07	Synovus Financial Corp	−0.06
8	SVB Financial Group	0.656	Wintrust Financial Corp	0.65	South State Corp	0.07	Texas Capital Bancshares Inc	−0.07	First Financial Bankshares Inc	−0.06
9	Fifth Third Bancorp	0.666	People's United Financial Inc	0.67	Signature Bank	0.07	Community Bank System Inc	−0.06	Prosperity Bancshares Inc	−0.06
10	First Horizon Corp (Tennessee)	0.672	Huntington Bancshares Inc	0.69	Texas Capital Bancshares Inc	0.07	U.S. Bancorp	−0.06	BOK Financial Corp	−0.05

Note: This table presents the consolidation of the top 10 large banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 18
Top 5 of FRED's macroeconomic variables that best explain banking factors using EBITDA.

Banking Factors	Group	Description	R^2_{Adj}
All			
Factor 1	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.58
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.54
	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.54
	Housing	All-Transactions House Price Index for the United States (Index 1980 Q1 = 100)	0.53
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.51
Factor 2	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.83
	Employment and Unemployment	All Employees: Information Services (Thousands of Persons)	0.64
	Employment and Unemployment	All Employees: Nondurable goods (Thousands of Persons)	0.63
	Employment and Unemployment	Help-Wanted Index	0.50
	Employment and Unemployment	All Employees: Manufacturing (Thousands of Persons)	0.46
Factor 3	Money and Credit	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.38
	Housing	Housing Starts in Midwest Census Region (Thousands of Units)	0.32
	Housing	New Private Housing Units Authorized by Building Permits (Thousands of Units)	0.31
	Housing	New Private Housing Units Authorized by Building Permits in the West Census Region (Thousands, SAAR)	0.29
	NIPA	Real private fixed investment: Residential (Billions of Chained 2012 Dollars), deflated using PCE	0.29

Note: This table presents the macroeconomic series of the FRED-QD most correlated with each of the banking factors estimated according to the R^2_{Adj} criterion. Each of the series is classified into a group determined by Stock & Watson (2012).

Table 19
FRED's top 5 macroeconomic variables that best explain the estimated banking factors with respect to EBITDA by market size.

Banking Factors	Group	Descriptionn	R^2_{Adj}
Small			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.58
	Housing	All-Transactions House Price Index for the United States (Index 1980 Q1 = 100)	0.43
	Household Balance Sheets	Liabilities of Households and Nonprofit Organizations Relative to Personal Disposable Income (Percent)	0.42
	Non-Household Balance Sheets	Real Nonfinancial Noncorporate Business Sector Liabilities (Billions of 2012 Dollars), Deflated by Implicit Price Deflator for Business Sector IPDBS	0.40
	Money and Credit	Real Real Estate Loans, All Commercial Banks (Billions of 2012 U.S. Dollars), deflated by Core PCE	0.35
Factor 2	Employment and Unemployment	Help-Wanted Index	0.74
	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.56
	Household Balance Sheets	Net Worth of Households and Nonprofit Organizations Relative to Disposable Personal Income (Percent)	0.48
	Employment and Unemployment	All Employees: Information Services (Thousands of Persons)	0.46
	Employment and Unemployment	All Employees: Nondurable goods (Thousands of Persons)	0.44
Factor 3	Money and Credit	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.33
	Money and Credit	Total Consumer Credit Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.31
	NIPA	Real Government Consumption Expenditures and Gross Investment: Federal (Percent Change from Preceding Period)	0.24
	Money and Credit	Total Consumer Loans and Leases Outstanding Owned and Securitized by Finance Companies (Millions of Dollars)	0.20
	Housing	Housing Starts: Total: New Privately Owned Housing Units Started (Thousands of Units)	0.18
Medium			
Factor 1	Household Balance Sheets	Real Total Liabilities of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.57
	Housing	All-Transactions House Price Index for the United States (Index 1980 Q1 = 100)	0.56
	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.56
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.54
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.53
Factor 2	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.84
	Employment and Unemployment	All Employees: Information Services (Thousands of Persons)	0.56
	Employment and Unemployment	All Employees: Nondurable goods (Thousands of Persons)	0.53
	Employment and Unemployment	All Employees: Manufacturing (Thousands of Persons)	0.41
	Employment and Unemployment	Help-Wanted Index	0.40

(*continued on next page*)

Table 19 (*continued*)

Banking Factors	Group	Descriptionn	R^2_{Adj}
Factor 3	Housing	Housing Starts in Midwest Census Region (Thousands of Units)	0.42
	NIPA	Real personal consumption expenditures: Durable goods (Billions of Chained 2012 Dollars), deflated using PCE	0.36
	Housing	New Private Housing Units Authorized by Building Permits (Thousands of Units)	0.32
	Money and Credit	Total Real Nonrevolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	0.32
	Housing	New Private Housing Units Authorized by Building Permits in the South Census Region (Thousands, SAAR)	0.28
Large			
Factor 1	Money and Credit	Total Real Revolving Credit Owned and Securitized, Outstanding (Billions of 2012 Dollars), deflated by Core PCE	
	Industrial Production	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)	0.64
	Other	University of Michigan: Consumer Sentiment (Index 1st Quarter 1966 = 100)	0.58
	Industrial Production	Capacity Utilization: Total Industry (Percent of Capacity)	0.53
	Household Balance Sheets	Real Real Estate Assets of Households and Nonprofit Organizations (Billions of 2012 Dollars), deflated by Core PCE	0.49
Factor 2	Employment and Unemployment	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing (Hours)	0.70
	Employment and Unemployment	All Employees: Information Services (Thousands of Persons)	0.66
	Employment and Unemployment	All Employees: Nondurable goods (Thousands of Persons)	0.64
	Employment and Unemployment	All Employees: Manufacturing (Thousands of Persons)	0.45
	Employment and Unemployment	Help-Wanted Index	0.40
Factor 3	Housing	New Private Housing Units Authorized by Building Permits (Thousands of Units)	0.67
	Interest Rates	3-Month Commercial Paper Minus 3-Month Treasury Bill, secondary market (Percent)	0.64
	NIPA	Real private fixed investment: Residential (Billions of Chained 2012 Dollars), deflated using PCE	0.59
	Housing	New Private Housing Units Authorized by Building Permits in the West Census Region (Thousands, SAAR)	0.57
	Housing	New Private Housing Units Authorized by Building Permits in the South Census Region (Thousands, SAAR)	0.51

Note: This table presents the macroeconomic series of the FRED-QD most correlated according to the $\boldsymbol{R^2_{Adj}}$ criterion with each of the banking factors estimated from EBITDA. Each of the series is classified into a group determined by Stock & Watson (2012). The results are grouped into sections of small, medium, and large banks according to their market capitalization.

Table 20
Top 10 banks according to the estimated parameters of the model by factors using EBITDA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Macatawa Bank Corp	0.968	Truist Financial Corp	78.00	Investors Bancorp Inc	12.20	Truist Financial Corp	4.83	First United Corp	13.31
2	Mercantile Bank Corp	0.965	Benchmark Bankshares Inc	73.84	First United Corp	7.89	OptimumBank Holdings Inc	3.48	OptimumBank Holdings Inc	10.23
3	Western Alliance Bancorp	0.963	Fifth Third Bancorp	70.11	First Financial Northwest Inc	4.82	Fifth Third Bancorp	3.24	Patriot National Bancorp Inc	5.26
4	Capital City Bank Group Inc	0.963	Citizens Financial Corp	66.38	First National Bank Alaska	4.28	Southern Banc Company Inc	3.10	Limestone Bancorp Inc	4.18
5	Sierra Bancorp	0.941	First Republic Bank	64.98	Central Pacific Financial Corp	4.12	Chemung Financial Corp	2.97	Orrstown Financial Services Inc	3.26
6	Trico Bancshares	0.940	CIT Group Inc	63.42	Synovus Financial Corp	4.00	First Republic Bank	2.68	University Bancorp Inc (MICHIGAN)	3.13
7	Fulton Financial Corp	0.933	First Bancorp Inc	61.35	United Community Banks Inc	3.95	Limestone Bancorp Inc	2.48	Malvern Bancorp Inc	2.77
8	Synovus Financial Corp	0.931	Berkshire Bancorp Inc	60.75	Preferred Bank	3.83	First Farmers and Merchants Corp	1.99	Univest Financial Corp	2.68
9	Seacoast Banking Corporation of Florida	0.928	Westamerica Bancorp	59.91	Hanmi Financial Corp	3.75	First Midwest Bancorp Inc	1.98	Fauquier Bankshares Inc	2.66
10	Ameris Bancorp	0.922	Prosperity Bancshares Inc	58.18	OptimumBank Holdings Inc	3.57	Orrstown Financial Services Inc	1.94	FNCB Bancorp Inc	2.54
Lower ranking of banks										
1	Pathfinder Bancorp Inc (MARYLAND)	−0.098	First National Bank Alaska	−62.07	Mackinac Financial Corp	−1.71	First National Bank Alaska	−12.67	First National Bank Alaska	−11.65
2	Berkshire Bancorp Inc	−0.098	OptimumBank Holdings Inc	−18.04	OFG Bancorp	−0.85	Investors Bancorp Inc	−6.54	Investors Bancorp Inc	−11.29
3	Southside Bancshares Inc	−0.074	Hilltop Holdings Inc	−10.78	University Bancorp Inc (MICHIGAN)	−0.78	Mackinac Financial Corp	−4.25	Hilltop Holdings Inc	−9.13
4	City Holding Co	−0.072	First United Corp	−8.18	Premier Financial Bancorp Inc	−0.64	Signature Bank	−2.61	Financial Institutions Inc	−7.02
5	Hilltop Holdings Inc	−0.003	Patriot National Bancorp Inc	0.14	Signature Bank	−0.63	Pinnacle Financial Partners Inc	−2.45	CIT Group Inc	−5.65
6	First Business Financial Services Inc	0.059	Investors Bancorp Inc	1.54	First Republic Bank	−0.40	Preferred Bank	−2.42	Huntington Bancshares Inc	−2.41
7	Bancorp Inc	0.067	Southern Banc Company Inc	2.46	Chemung Financial Corp	−0.34	Financial Institutions Inc	−2.34	Seacoast Banking Corporation of Florida	−2.36
8	First Financial Corp	0.088	Pacific Mercantile Bancorp	8.95	Commercial National Financial Corp (Michigan)	−0.26	Pacific Premier Bancorp Inc	−2.12	OFG Bancorp	−2.31
9	Financial Institutions Inc	0.099	Mackinac Financial Corp	9.10	Croghan Bancshares Inc	−0.21	Premier Financial Bancorp Inc	−2.08	First Busey Corp	−2.13
10	Citizens Bancshares Corp	0.105	University Bancorp Inc (MICHIGAN)	12.34	Citizens Community Bancorp Inc	−0.21	SB Financial Group Inc	−1.97	Citigroup Inc	−2.07

Note: This table presents the consolidation of the top 10 banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 21
Top 10 small banks according to the estimated parameters of the model by factors using EBITDA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	First Northern Community Bancorp	0.936	Benchmark Bankshares Inc	73.37	First United Corp	14.83	First United Corp	16.47	First United Corp	18.90
2	Northwest Indiana Bancorp	0.901	Citizens Financial Corp	66.06	OptimumBank Holdings Inc	9.63	First Financial Northwest Inc	6.84	OptimumBank Holdings Inc	15.76
3	Fentura Financial Inc	0.898	Berkshire Bancorp Inc	60.75	First Financial Northwest Inc	8.10	Mackinac Financial Corp	5.32	Patriot National Bancorp Inc	7.62
4	Old Point Financial Corp	0.894	Commercial National Financial Corp (Michigan)	55.60	Republic First Bancorp Inc	5.41	FNCB Bancorp Inc	4.07	Limestone Bancorp Inc	5.96
5	Penns Woods Bancorp Inc	0.879	Chemung Financial Corp	53.27	Patriot National Bancorp Inc	5.21	Patriot National Bancorp Inc	3.92	Malvern Bancorp Inc	3.77
6	Mid Penn Bancorp Inc	0.861	Ohio Valley Banc Corp	51.82	FNCB Bancorp Inc	4.64	Plumas Bancorp	3.48	Shore Bancshares Inc	3.69
7	First Farmers and Merchants Corp	0.857	Ames National Corp	51.59	Pacific Mercantile Bancorp	4.27	SB Financial Group Inc	3.38	Village Bank and Trust Financial Corp	3.35
8	Salisbury Bancorp Inc	0.851	LCNB Corp	49.86	Fentura Financial Inc	4.05	Colony Bankcorp Inc	3.33	Mackinac Financial Corp	3.18
9	United Security Bancshares	0.846	Auburn National Bancorporation Inc	47.87	Limestone Bancorp Inc	3.67	Fentura Financial Inc	3.24	Fentura Financial Inc	3.16
10	First Financial Northwest Inc	0.829	First Farmers and Merchants Corp	45.29	Southern Banc Company Inc	3.48	Community West Bancshares	3.17	BankFinancial Corp	2.84
Lower ranking of banks										
1	Berkshire Bancorp Inc	−0.137	OptimumBank Holdings Inc	−16.65	Mackinac Financial Corp	−5.10	Chemung Financial Corp	−4.99	Pacific Mercantile Bancorp	−4.72
2	Pathfinder Bancorp Inc (MARYLAND)	−0.081	First United Corp	−8.18	SB Financial Group Inc	−1.04	Southern Banc Company Inc	−3.93	Colony Bankcorp Inc	−3.70
3	First Business Financial Services Inc	0.056	Patriot National Bancorp Inc	0.14	Citizens Bancshares Corp	−0.56	Commercial National Financial Corp (Michigan)	−3.42	BNCCorp Inc	−3.18
4	Fauquier Bankshares Inc	0.063	Southern Banc Company Inc	2.32	Citizens Financial Services Inc	−0.53	Peoples Financial Corp	−2.59	First Financial Northwest Inc	−3.06
5	Citizens Bancshares Corp	0.091	Mackinac Financial Corp	8.79	Citizens Community Bancorp Inc	−0.17	Limestone Bancorp Inc	−2.10	First Capital Inc	−2.77
6	Landmark Bancorp Inc	0.096	Pacific Mercantile Bancorp	9.91	First Business Financial Services Inc	−0.14	Croghan Bancshares Inc	−1.98	First Robinson Financial Cororation	−2.71
7	Citizens Financial Corp	0.182	Ameriserv Financial Inc	14.53	Ameriserv Financial Inc	−0.06	United Bancorp Inc	−1.97	Southern Banc Company Inc	−2.38
8	First Robinson Financial Cororation	0.234	Village Bank and Trust Financial Corp	15.16	BNCCorp Inc	0.05	LCNB Corp	−1.84	Mid Penn Bancorp Inc	−1.89
9	Auburn National Bancorporation Inc	0.251	Uwharrie Capital Corp	17.76	Uwharrie Capital Corp	0.10	First Farmers and Merchants Corp	−1.74	Republic First Bancorp Inc	−1.77
10	Uwharrie Capital Corp	0.258	Citizens Bancshares Corp	18.88	Peoples Bancorp of North Carolina Inc	0.18	Citizens Holding Co	−1.54	C&F Financial Corp	−1.69

Note: This table presents the consolidation of the top 10 small banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 22
Top 10 medium banks according to the estimated parameters of the model by factors using EBITDA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Capital City Bank Group Inc	0.977	First Bancorp Inc	62.10	First National Bank Alaska	7.74	First National Bank Alaska	21.32	First National Bank Alaska	29.42
2	Mercantile Bank Corp	0.953	Westamerica Bancorp	59.97	Central Pacific Financial Corp	6.99	Preferred Bank	4.76	Financial Institutions Inc	12.57
3	Macatawa Bank Corp	0.944	West Bancorporation Inc	56.54	Preferred Bank	6.41	Financial Institutions Inc	4.05	OFG Bancorp	3.52
4	Sierra Bancorp	0.914	Parke Bancorp Inc	55.10	Hanmi Financial Corp	6.30	Premier Financial Bancorp Inc	3.95	Macatawa Bank Corp	2.79
5	Old Second Bancorp Inc	0.914	National Bankshares Inc	51.35	First Busey Corp	5.31	Hanmi Financial Corp	3.45	ConnectOne Bancorp Inc	2.56
6	Independent Bank Corp (Michigan)	0.905	Univest Financial Corp	51.28	Macatawa Bank Corp	5.28	Mercantile Bank Corp	3.30	First Busey Corp	2.49
7	Peoples Financial Services Corp	0.899	First of Long Island Corp	50.39	Mercantile Bank Corp	5.21	Central Pacific Financial Corp	3.19	Boston Private Financial Holdings Inc	2.39
8	Peapack-Gladstone Financial Corp	0.893	S&T Bancorp Inc	49.94	Financial Institutions Inc	5.05	Macatawa Bank Corp	3.10	Central Pacific Financial Corp	2.31
9	Trico Bancshares	0.893	City Holding Co	49.91	Independent Bank Corp (Michigan)	4.13	Enterprise Financial Services Corp	3.08	Mercantile Bank Corp	1.97
10	Heritage Commerce Corp	0.887	Central Valley Community Bancorp	47.99	Heritage Commerce Corp	3.46	Heritage Commerce Corp	2.88	West Bancorporation Inc	1.91
Lower ranking of banks										
1	Southside Bancshares Inc	−0.042	First National Bank Alaska	−68.72	Premier Financial Bancorp Inc	−1.30	Orrstown Financial Services Inc	−3.21	Orrstown Financial Services Inc	−5.92
2	City Holding Co	0.021	Financial Institutions Inc	12.71	OFG Bancorp	−1.26	First Bancorp Inc	−3.14	Univest Financial Corp	−4.98
3	First Financial Corp	0.063	Banc of California Inc	21.81	Bar Harbor Bankshares	−0.35	OFG Bancorp	−2.58	Premier Financial Bancorp Inc	−2.62
4	Bancorp Inc	0.073	Central Pacific Financial Corp	25.72	City Holding Co	−0.30	BCB Bancorp Inc	−2.57	Great Southern Bancorp Inc	−2.49
5	Univest Financial Corp	0.100	Boston Private Financial Holdings Inc	25.91	Southside Bancshares Inc	−0.27	Great Southern Bancorp Inc	−2.16	First Bancorp Inc	−2.48
6	Republic Bancorp Inc	0.147	Bancorp Inc	25.99	ConnectOne Bancorp Inc	−0.16	Peoples Financial Services Corp	−2.03	Southern First Bancshares Inc	−2.39
7	QCR Holdings Inc	0.156	Heritage Commerce Corp	26.26	German American Bancorp Inc	−0.12	Bancorp Inc	−2.03	Bancorp Inc	−2.35
8	Financial Institutions Inc	0.158	Macatawa Bank Corp	27.20	National Bankshares Inc	−0.07	Univest Financial Corp	−1.76	Sierra Bancorp	−2.23
9	First National Bank Alaska	0.220	Capital City Bank Group Inc	27.34	Citizens & Northern Corp	−0.02	Brookline Bancorp Inc	−1.62	BCB Bancorp Inc	−2.17
10	Northrim BanCorp Inc	0.274	Independent Bank Corp (Michigan)	28.31	First Financial Corp	0.00	OceanFirst Financial Corp	−1.61	Parke Bancorp Inc	−2.07

Note: This table presents the consolidation of the top 10 medium banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

Table 23
Top 10 large banks according to the estimated parameters of the model by factors using EBITDA.

	Bank	R^2_{Adj}	Bank	β_0	Bank	β_1	Bank	β_2	Bank	β_3
Top ranking of banks										
1	Western Alliance Bancorp	0.953	Truist Financial Corp	76.45	Investors Bancorp Inc	19.84	Truist Financial Corp	8.80	Truist Financial Corp	6.17
2	TCF Financial Corp	0.938	Fifth Third Bancorp	69.36	Synovus Financial Corp	6.19	Fifth Third Bancorp	6.36	Pinnacle Financial Partners Inc	4.66
3	Synovus Financial Corp	0.932	First Republic Bank	64.51	United Community Banks Inc	6.18	First Republic Bank	4.47	Investors Bancorp Inc	3.82
4	Truist Financial Corp	0.930	CIT Group Inc	61.07	Seacoast Banking Corporation of Florida	5.59	First Midwest Bancorp Inc	4.37	Synovus Financial Corp	2.87
5	Seacoast Banking Corporation of Florida	0.929	Prosperity Bancshares Inc	58.18	CIT Group Inc	4.88	Credicorp Ltd	3.78	First Midwest Bancorp Inc	2.67
6	Umpqua Holdings Corp	0.924	Bank Ozk	55.22	PacWest Bancorp	3.84	Trustmark Corp	2.94	PacWest Bancorp	2.63
7	Fulton Financial Corp	0.911	Lakeland Financial Corp	55.05	First Bancorp	3.78	First Bancorp	2.63	First Bancorp	2.48
8	Huntington Bancshares Inc	0.890	Cathay General Bancorp	53.30	First Horizon Corp (Tennessee)	3.39	Valley National Bancorp	2.60	United Community Banks Inc	2.15
9	United Bankshares Inc	0.884	United Bankshares Inc	52.84	Cathay General Bancorp	3.34	Heartland Financial USA Inc	2.55	First Republic Bank	1.98
10	Hope Bancorp Inc	0.883	East West Bancorp Inc	51.46	Huntington Bancshares Inc	3.12	First Horizon Corp (Tennessee)	2.38	Pacific Premier Bancorp Inc	1.85
Lower ranking of banks										
1	First Financial Bankshares Inc	0.173	Hilltop Holdings Inc	−10.78	First Republic Bank	−1.17	Investors Bancorp Inc	−7.02	Hilltop Holdings Inc	−30.30
2	UMB Financial Corp	0.230	Investors Bancorp Inc	−5.98	Hilltop Holdings Inc	−0.63	Signature Bank	−5.20	Citigroup Inc	−6.25
3	Simmons First National Corp	0.231	United Community Banks Inc	19.41	Signature Bank	−0.36	Pinnacle Financial Partners Inc	−4.01	Huntington Bancshares Inc	−4.12
4	Hancock Whitney Corp	0.255	Citigroup Inc	22.80	Truist Financial Corp	−0.09	Pacific Premier Bancorp Inc	−3.89	First Horizon Corp (Tennessee)	−3.94
5	CIT Group Inc	0.262	First Bancorp	22.97	UMB Financial Corp	−0.05	Home BancShares Inc	−2.85	Webster Financial Corp	−3.74
6	Hilltop Holdings Inc	0.301	Popular Inc	23.70	First Financial Bankshares Inc	0.12	Atlantic Union Bankshares Corp	−2.50	Seacoast Banking Corporation of Florida	−3.43
7	Trustmark Corp	0.317	Seacoast Banking Corporation of Florida	24.01	Prosperity Bancshares Inc	0.13	Texas Capital Bancshares Inc	−1.96	East West Bancorp Inc	−2.23
8	BOK Financial Corp	0.362	Ameris Bancorp	27.31	Towne Bank	0.27	SVB Financial Group	−1.51	Regions Financial Corp	−1.92
9	South State Corp	0.377	UMB Financial Corp	27.46	Cullen/Frost Bankers Inc	0.31	KeyCorp	−1.50	Sterling Bancorp	−1.88
10	Heartland Financial USA Inc	0.381	Banner Corp	27.92	International Bancshares Corp	0.33	JPMorgan Chase & Co	−1.48	First Financial Bancorp	−1.81

Note: This table presents the consolidation of the top 10 large banks according to the risk estimators associated with the estimated factors. Upper panel shows the banks most vulnerable. Lower panel shows the banks most robust respect to shocks macroeconomics.

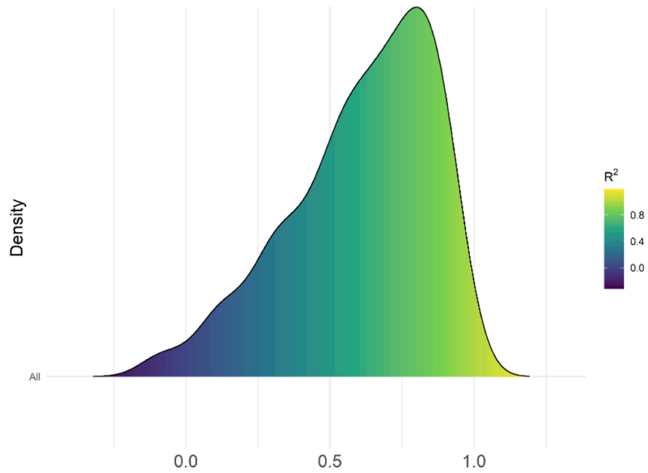

Fig. 12. Distribution of R^2 of the model by factors. **Note:** This figure shows the density about $\boldsymbol{R}^2_{Adj}$ for the set of regressions of the dynamic factor models from EBITDA.

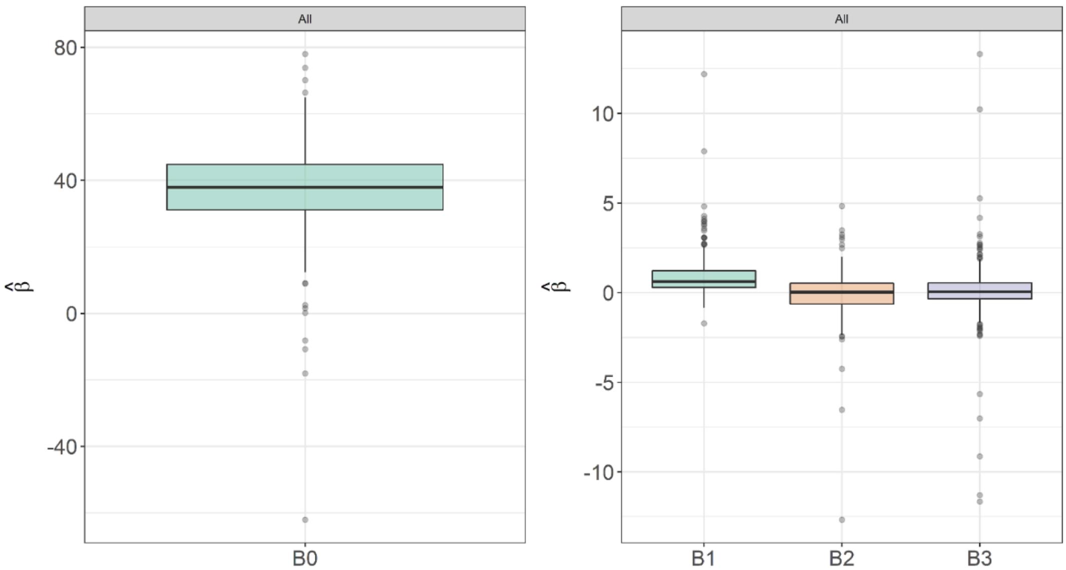

Fig. 13. Distribution of model estimators by factors from ROA. **Note:** The left panel shows the distribution of the $\boldsymbol{\beta}_0$ estimator that represents the fixed effect. The right panel shows the distribution of the estimates of the effect $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \boldsymbol{\beta}_3$ of the banking factors.

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