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# The Impact of Risk Exposure and Environmental Conditions on European Banking Efficiency

Pilar Gargallo[1] | Jordi Moreno[2] | Manuel Salvador[1]

[1]Facultad de Economía y Empresa, Departamento de Economía Aplicada, Universidad de Zaragoza, Member of the IEDIS (Instituto Universitario de Investigación en Empleo, Sociedad y Sostenibilidad), Zaragoza, Spain | [2]Facultat de Dret, Economia i Turisme, Departament d'Economia i Empresa, Universitat de Lleida, Lleida, Spain

**Correspondence:** Jordi Moreno (jordi.moreno@udl.cat)

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## ABSTRACT

This study investigates the determinants of bank cost efficiency in Europe by applying a dynamic Bayesian stochastic frontier approach. We distinguish between two conceptually and empirically separate components of efficiency: (1) an intrinsic component, driven by internal bank features such as size and risk exposure, and (2) an extrThis study investigates the determinantsnsic component, shaped by broader sectoral and macroeconomic conditions. The results confirm that cost efficiency is significantly influenced by intrinsic factors, as well as by environmental conditions. The relative influence of intrinsic and extrinsic factors varies across countries and over time, highlighting the importance of context-specific and adaptive policy and managerial responses.

**JEL Classification:** C11, C23, G14, G21, G32

## 1 | Introduction

Risk-taking has been identified as a relevant element of the banking production process, which should be properly modelled into efficiency measurement (Sarmiento and Galán 2017). Previous evidence shows that failure to account for risk-taking may lead to biased estimations of bank efficiency and misleading estimates of scale economies and cost elasticities (Koetter 2008; Hughes and Mester 2013; Malikov et al. 2015). Despite this evidence, it remains ambiguous to what extent and in what manner exposure to banking risks affects the performance of banks. Understanding this relationship is paramount, particularly given the heightened competition in the banking sector, compelling banks to operate closer to the efficient frontier.

Similarly, bank size is another relevant micro-level factor that is often associated with efficiency gains through economies of scale or scope (S. Chen et al. 2020). When it comes to bank size, managers need to strike the right balance, taking advantage of economies of scale while avoiding excessive managerial costs resulting from overly complex organizational structures (Krause et al. 2017).

The dynamics of the sector also play a crucial role in the bank performance. For example, in a highly competitive environment, market pressure and the concentration of the banking sector can affect the efficiency and profitability of financial institutions (Kozak and Wierzbowska 2021). In addition, also national-level regulatory frameworks, economic policies and the economic conditions of the country directly affect the quality of banks' assets and their ability to generate income (Barth et al. 2013). These specific environmental conditions hinder banks in different countries from selecting from the full set of technologically optimal input–output mixes in the potential technology set.

Against this background, this study seeks to bridge the gap between internal and external determinants of bank performance by assessing cost efficiency in European financial institutions. While previous studies have offered valuable insights into bank efficiency (Silva et al. 2016; Psillaki and Mamatzakis 2017; Pérez-Cárceles et al. 2019; Do Van Anh. 2022) and the role of risks-taking (Delis et al. 2017; Sarmiento and Galán 2017; Ding and Sickles 2018) important gaps remain—particularly regarding the joint and dynamic influence of internal and external factors over time. To address this, we examine whether inefficiency arises from micro-level factors, broader sectoral and macroeconomic conditions, or from the combined influence of both.

To that end, we decompose cost efficiency into two distinct components: an intrinsic component, reflecting bank-specific characteristics, and an extrinsic component, capturing the influence of the operational environment. Our model captures the dynamic evolution of these components, allowing us to isolate and quantify how internal management practices and external structural conditions interact to shape banking performance over time. In our framework, intrinsic efficiency is dynamically explained by factors such as size and exposure to key risks, including credit, liquidity, capitalization and market risks. Meanwhile, extrinsic efficiency is shaped by time-varying industry-level and macroeconomic variables—such as market concentration, financial depth, non-performing loans (NPLs), the strength of legal rights, GDP growth, GDP per capita and inflation. This distinction enables a more detailed understanding of whether inefficiency is primarily driven by internal or external forces—or a combination of both.

This study contributes to the existing literature in several important ways. First, it sheds light on the temporal evolution of cost efficiency by capturing the dynamic interaction between internal and external performance drivers. Second, through the application of a Bayesian stochastic frontier model, the study provides a robust analytical framework that accounts for parameter uncertainty and latent inefficiency, offering a more refined perspective on how bank efficiency evolves in response to both microeconomic and macroeconomic factors. Third, by decomposing cost efficiency into intrinsic and extrinsic components, the research pinpoints the sources of inefficiency, allowing a clear distinction between those rooted in managerial decisions and those shaped by external structural conditions.

In addition, while previous studies have acknowledged the role of environmental factors in shaping bank efficiency (e.g., Fiordelisi et al. 2011; Barth et al. 2013; M. Chen et al. 2017a), our work represents a significant advancement by quantifying the share of each bank's efficiency attributable to internal versus external drivers. To the best of our knowledge, no previous study has provided this type of dynamic efficiency decomposition.

Furthermore, we move beyond traditional efficiency estimation by analysing how the main determinants of inefficiency—such as risk exposure, bank size and macroeconomic conditions—ultimately influence total cost levels. This allows us to trace the full transmission channel from observable factors, through their impact on intrinsic and extrinsic efficiency, to their marginal effects on cost outcomes.

To conduct this analysis, we apply a Bayesian stochastic frontier model to an unbalanced panel of commercial banks operating in the 28 European Union countries from 2004 to 2020. The Bayesian approach has been widely applied in the statistical analysis of stochastic frontier models (Fernández et al. 1997; Koop et al. 1997; Koop and Steel 2001; Tsionas 2002; Feng and Zhang 2014; Galán et al. 2015; Gallizo et al. 2016, 2017; Assaf and Tsionas 2018; Skevas et al. 2018; Skevas 2020; Cortés-García and Pérez-Rodríguez 2024, among others). This approach offers greater flexibility in modelling the inefficiency terms of the model, as it simplifies the handling of latent variables in Bayesian inference. Furthermore, it allows for inference about model parameters in finite samples and enables comparisons of the goodness-of-fit between non-nested models without relying on asymptotic procedures, which may be of questionable validity in this context.

In this paper, following previous approaches in production models (Skevas et al. 2018; Skevas 2020), we adopt a logit-type parametrization for the inefficiency terms, projecting them from the unit interval onto the real line. This approach helps us avoid the criticism associated with imposing a dynamic regression model with exogenous variables on a bounded variable like efficiency (Tsionas 2006). Overall, this enhances both the robustness and realism of our study.

The results confirm that cost efficiency is significantly influenced by risk exposure, size and environmental conditions. Regarding risk exposure, the results indicate that different types of risk do not exert uniform effects on efficiency; their impact varies both, in direction and intensity. As for environmental conditions, factors such as market concentration, financial depth, the strength of legal rights and the inflation rate are found to significantly influence extrinsic efficiency. It is also appreciated a decline in banking efficiency in most European countries during this period. This decline is explained by a slight deterioration in intrinsic efficiency and, more importantly, a decline in extrinsic efficiency driven by changes in the operating environment. It was also observed that, in some countries, intrinsic factors played a greater role in explaining efficiency, while extrinsic factors were more important in others. Furthermore, the importance of these factors fluctuates over time.

These findings underscore the importance of adopting context-specific strategies that simultaneously consider both bank-level characteristics and the broader sectoral and macroeconomic environment. This decomposition enables us to estimate the true scope for improvement through managerial action and to identify where structural reforms may be most needed. By accounting for both internal and external drivers of efficiency, our integrated perspective offers actionable insights for bank managers, regulators and policymakers. This enhances the practical and managerial relevance of the analysis and provides valuable guidance for designing effective interventions to improve banking performance across diverse institutional settings.

The rest of the paper is organized as follows: Section 2 describes the data and variables; Section 3 details the methodology; Section 4 discusses the empirical results, and the final section presents conclusions. Supporting Information contains additional results on the dynamics of country-level and individual bank efficiencies, as well as the results of several robustness analyses conducted throughout the paper.

## 2 | Data and Variables

### 2.1 | Data

Bank data were obtained from the Orbis Bank Focus database for the period 2004–2016 and from the Orbis database for the period 2017–2020. Both databases are developed by Bureau van Dijk and are widely used in the literature (Huang et al. 2015; Doan et al. 2018; Pérez-Cárceles et al. 2019, among many others). Particularly, we selected the commercial banks included in these databases for which data needed to estimate efficiency levels were available for at least 4 years, between 2004 and 2020. In addition, when less than four observations were available for a country/year, these data were also removed, as they were considered insufficient to estimate the efficiency for that country in that year.

As in previous studies (Kasman and Yildirim 2006; Brissimis et al. 2008; Gallizo et al. 2016, 2017), we focused on commercial banks because, as is argued in Demirguc-Kunt et al. (2004), doing so enhances the comparability of banks in our sample. It is important to note that other types of banks—such as savings, cooperative and investment banks—often pursue objectives beyond pure profitability, which can influence their estimated efficiency. Consequently, including these institutions may result in misleading conclusions. As in Gallizo et al. (2016), we included all active and dissolved banks for which data were available (as opposed to only active banks, as in other studies) to see the full effects of the financial crisis; we also aimed to weaken a possible survival bias. Whilst macroeconomic variables are retrieved from World Development Indicators (World Bank).

The sample comprised 1107 banks from 28 European countries in the period 2004–2020. In Table 1, we present the distribution of observations by country and by year. This table provides a comprehensive view of the distribution of banks throughout the European Union and how it has evolved over the specified period. Noticeable imbalances are apparent, with countries such as France consistently having a high number of banks each year, while others, like Malta or Estonia, have significantly fewer banks. For example, in the case of Lithuania, there are only 96 observations, and it is important to note that data for the last 4 years are missing due to insufficient information for fewer than four banks. The study encompasses 11,059 observations, representing a substantial sample size compared to other literature exploring bank efficiency in the European Union, where some studies consider only a fraction of our sample, typically focusing on 4 or 5 years and exclusively on active banks.

### 2.2 | Variables

#### 2.2.1 | Input and Output Variables

A critical step in the analysis of banking efficiency is defining the inputs and outputs of the production process. This is because there is no general agreement in the banking literature about which are the most appropriate input and output variables (Ahm and Le 2014). This is not straightforward in the case of banking models because, deposits, in particular, have characteristics of both inputs and outputs (see Tortosa-Ausina 2002). In the literature, three major approaches prevailed for modelling the technological process of banks: production, value-added and intermediation. The intermediation approach is the most commonly applied in the literature (Zelenyuk and Zelenyuk 2021). According to this, the role of a bank is to transform savings (mostly deposits) into investments (mostly loans). The bank is viewed as a decision-making unit (DMU) which collects deposits with labour and capital and produces loans and other earning assets (Sealey and Lindley 1977). The value-added approach considers that the role of a bank is to create income with a difference between earnings from outputs and cost from inputs; in consequence, the value-added approach treats deposits as outputs because they imply the creation of value added. Berger and Humphrey (1992) proposed a modified version of the value-added approach that incorporates both the inputs and outputs characteristics of deposits by including them as both inputs and outputs in their function.

Previous studies such as those by Gallizo et al. (2016, 2017) compared to the use of the intermediation approach and the modified version of the value-added approach for estimating bank efficiency in European Union countries. Using Bayesian statistical tools for model comparison and selection, they found that the modified version of the value-added approach provided a better goodness-of-fit to the available data for both cost efficiency and profit efficiency. Based on these results, in this paper, we have adopted an approach based on the modified version of the value-added approach, whereby deposits (customer and bank deposits) have been used as input and output simultaneously in the model.

In addition to the consideration of deposits, another relevant issue is the treatment of off-balance-sheet (OBS) items. Since the beginning of the century, banks around the world have diversified away from traditional financial intermediation activities in the off-balance sheet and fees and commissions generating activities (Karray and Chichti 2013). Berger and Mester (1997) already considered that off-balance-sheet items should be included because they are effective substitutes for direct lending and can be a source of comparable income. Models that ignore nontraditional outputs penalized banks heavily involved in such activities, because resources that used to produce these nontraditional services were included in the input vector without accommodating the relevant variables in the output vector (Rogers 1998; Doan et al. 2018). In consequence, many studies have included these operations in the output vector (Barth et al. 2013; M. Chen et al. 2022; Pérez-Cárceles et al. 2019). However, many other studies continue to estimate efficiency frontiers without accounting for such nontraditional activities (Borauzima and Muller 2023; Nurboja and Košak 2017). Therefore, there is no consensus in the literature as regards the inclusion of these activities in the output vector. A handful of studies that included a measure of OBS activities in the specification of banks' output, highlighting that traditional bank efficiency measures that exclude OBS items are less accurate indicators of true bank efficiency (Casu and Girardone 2005). In consequence, we also opted to include this variable into the model. Since the off-balance sheet activities are generally four or five times greater than the balance sheet times,

**TABLE 1** | Distribution of banks by country and by year.

| Country | | Year | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Banks | Total |
| Austria | AUT | 40 | 41 | 42 | 42 | 42 | 45 | 45 | 45 | 44 | 40 | 32 | 33 | 28 | 10 | 10 | 10 | 9 | 54 | 558 |
| Belgium | BEL | 13 | 18 | 19 | 19 | 17 | 17 | 17 | 14 | 17 | 18 | 17 | 19 | 19 | 19 | 18 | 18 | 18 | 31 | 297 |
| Bulgaria | BUL | 7 | 10 | 10 | 12 | 13 | 15 | 17 | 16 | 16 | 13 | 17 | 17 | 16 | 13 | 13 | 12 | 12 | 22 | 229 |
| Croatia | CRO | 20 | 22 | 25 | 25 | 30 | 29 | 29 | 28 | 28 | 25 | 23 | 23 | 22 | 17 | 15 | 14 | 14 | 33 | 389 |
| Cyprus | CYP | 7 | 7 | 7 | 7 | 6 | 5 | 5 | 4 | 4 | 4 | 15 | 17 | 19 | 18 | 18 | 17 | 17 | 24 | 177 |
| Czech Republic | CZE | 14 | 15 | 15 | 15 | 13 | 14 | 14 | 13 | 14 | 13 | 18 | 18 | 18 | 18 | 17 | 17 | 17 | 23 | 263 |
| Denmark | DNK | 35 | 41 | 43 | 43 | 41 | 40 | 34 | 34 | 32 | 27 | 27 | 28 | 28 | 25 | 24 | 24 | 21 | 49 | 547 |
| Estonia | EST | 5 | 5 | 5 | 5 | 4 | 4 | 6 | 6 | 6 | 6 | 7 | 6 | 6 | 6 | 4 | 4 | 4 | 8 | 89 |
| Finland | FIN | | 4 | 4 | 4 | 6 | 7 | 8 | 8 | 8 | 6 | 7 | 11 | 12 | 13 | 13 | 13 | 13 | 18 | 137 |
| France | FRA | 52 | 72 | 79 | 86 | 82 | 82 | 81 | 85 | 92 | 86 | 84 | 85 | 82 | 78 | 76 | 74 | 73 | 124 | 1349 |
| Germany | GER | 73 | 79 | 83 | 88 | 81 | 87 | 90 | 89 | 90 | 71 | 61 | 59 | 55 | 25 | 22 | 22 | 20 | 113 | 1095 |
| Greece | GRE | 12 | 14 | 15 | 15 | 16 | 16 | 16 | 11 | 11 | 7 | 6 | 6 | 6 | 5 | 5 | 5 | 5 | 16 | 171 |
| Hungary | HUN | 15 | 15 | 15 | 16 | 15 | 16 | 15 | 14 | 14 | 13 | 14 | 14 | 13 | 11 | 10 | 10 | 10 | 22 | 230 |
| Ireland | IRE | 4 | 8 | 9 | 9 | 9 | 8 | 8 | 7 | 7 | 6 | 8 | 8 | 8 | 9 | 9 | 9 | 8 | 14 | 134 |
| Italy | ITA | | 73 | 77 | 83 | 85 | 87 | 85 | 80 | 78 | 71 | 58 | 60 | 62 | 49 | 46 | 43 | 42 | 116 | 1079 |
| Latvia | LAT | 12 | 14 | 15 | 15 | 15 | 16 | 17 | 14 | 14 | 15 | 15 | 14 | 15 | 12 | 12 | 12 | 12 | 22 | 239 |
| Lithuania | LIT | 7 | 7 | 8 | 8 | 8 | 9 | 9 | 8 | 7 | 7 | 6 | 6 | 6 | | | | | 9 | 96 |
| Luxembourg | LUX | 50 | 53 | 54 | 60 | 58 | 54 | 50 | 44 | 41 | 31 | 27 | 25 | 23 | 8 | 7 | 5 | 5 | 66 | 595 |
| Malta | MAL | | 3 | 3 | 3 | 4 | 5 | 5 | 6 | 6 | 6 | 7 | 7 | 7 | 6 | 6 | 6 | 6 | 8 | 86 |
| Netherlands | NTH | 11 | 14 | 15 | 16 | 18 | 20 | 19 | 19 | 18 | 17 | 18 | 19 | 18 | 17 | 16 | 16 | 14 | 28 | 285 |
| Poland | POL | 13 | 17 | 17 | 18 | 24 | 26 | 25 | 24 | 22 | 16 | 25 | 25 | 24 | 23 | 22 | 21 | 20 | 43 | 362 |
| Portugal | POR | | 11 | 12 | 14 | 15 | 15 | 16 | 15 | 16 | 13 | 16 | 16 | 15 | 15 | 14 | 14 | 14 | 23 | 231 |
| Romania | ROM | 14 | 15 | 16 | 17 | 17 | 18 | 20 | 19 | 17 | 13 | 18 | 18 | 18 | 17 | 17 | 16 | 16 | 30 | 286 |
| Slovakia | SLK | 8 | 10 | 10 | 10 | 11 | 11 | 11 | 10 | 10 | 10 | 10 | 10 | 10 | 6 | 6 | 6 | 6 | 14 | 155 |
| Slovenia | SLV | 11 | 13 | 13 | 13 | 13 | 14 | 13 | 13 | 13 | 12 | 10 | 9 | 9 | 10 | 10 | 10 | 9 | 17 | 195 |
| Spain | SPA | 12 | 21 | 23 | 23 | 25 | 23 | 26 | 26 | 25 | 22 | 35 | 35 | 37 | 37 | 33 | 32 | 31 | 52 | 466 |
| Sweden | SWE | 9 | 11 | 11 | 11 | 15 | 16 | 18 | 19 | 19 | 18 | 20 | 19 | 19 | 17 | 17 | 17 | 17 | 23 | 273 |
| United Kingdom | UKG | 36 | 56 | 58 | 64 | 66 | 67 | 67 | 66 | 69 | 58 | 69 | 69 | 67 | 61 | 60 | 59 | 54 | 105 | 1046 |
| Number of banks | | 480 | 669 | 703 | 741 | 749 | 766 | 766 | 737 | 738 | 644 | 670 | 676 | 662 | 545 | 520 | 506 | 487 | 1107 | 11,059 |

their inclusion in efficiency models in notional values can cause a bias (Karray and Chichti 2013). Therefore, in many studies such as those of Barth et al. (2013), Huang et al. (2015) or Pérez-Cárceles et al. (2019) researchers used noninterest income as a proxy for nontraditional bank operations. This proxy is used in our study.

Consequently, in our model we use the following four outputs: Deposits (customer deposits + bank deposits), Net Loans (gross loans – reserves for impaired loans), Other Earning Assets (total earning assets – net loans) and Off-Balance Sheet items (noninterest income). Regarding inputs prices, and following M. Chen et al. (2022), Doan et al. (2018), Hasan and Marton (2003), Silva et al. (2016) or Sun and Chang (2011), we used two inputs prices. These are the Price of Funds, measured by the ratio of interest expenses to total deposits, and Price of Capital, measured by the ratio of noninterest expenses (salaries and other operating expenses) to total fixed assets.[1]

### 2.2.2 | Bank Characteristics

In this section, we describe the bank-specific characteristics that influence cost efficiency, focusing on variables that are particularly relevant to internal managerial decisions within financial institutions. We discuss how factors such as banking risk exposure and bank size can affect cost efficiency, providing a detailed insight into the internal factors that affect the bank's performance. Additionally, we provide an overview of the expected direction of these relationships to offer a sense of the logic underlying these associations.

In terms of risk, and in line with Sarmiento and Galán (2017), we have included specific measures for exposure to credit risk, liquidity risk, equity risk and market risk.

Exposure to credit risk is evaluated through the ratio of loan loss provisions to loans, capturing the uncertainty associated with loan repayment. Given that a significant portion of a bank's earning assets is in the form of loans, issues with loan quality have historically been a leading cause of bank failures (Agoraki and Malindretou 2013). While using NPLs as a proxy for credit risk might have been preferable due to concerns about income smoothing with loan loss provisions (Laeven and Majnoni 2003), missing data required the adoption of this second-best solution.

A higher ratio reflects a greater degree of risk exposure, leading to heightened expenses for monitoring and managing problematic loans. Although there is potential for additional profits from higher-risk loans, especially in normal circumstances, this potential diminishes during crisis years, increasing the likelihood of extra losses. In consequence, an inverse relationship between credit risk and cost efficiency is expected.

Focusing on exposure to liquidity risk, it is assessed through the liquidity ratio (Cash & Balances with central banks to Total Assets). Here, a higher ratio reflects lower exposure to liquidity risk. In financial terms, liquidity risk pertains to an institution's potential difficulty in meeting short-term financial obligations. A heightened liquidity ratio indicates that the financial institution holds a substantial amount of liquid assets relative to its short-term liabilities. This serves as a precautionary measure, ensuring that the institution possesses the necessary resources to cover unforeseen demands or losses. When a bank's liquidity is insufficient, it must secure new funds to meet requirements, resulting in increased costs and reduced efficiency (Cao et al. 2023). Consequently, a positive association between liquidity and cost efficiency could be expected. However, to maintain high liquidity positions without reducing its productive activity, the bank may be forced to pay higher prices to attract more funds. This can be particularly true for smaller banks during times of crisis, as they may generate less customer confidence. In this line, some works such as Sakouvogui and Shaik (2020) for US commercial banks and Sarmiento and Galán (2014) for Colombian domestic banks find a negative effect of liquidity on cost efficiency.

Exposure to equity risk (or capitalization) is measured as equity divided by total assets and is considered a proxy for regulatory conditions that may affect banking efficiency. Higher capitalization in banks is associated with a lower likelihood of failure and allows them to secure liabilities at lower costs (M. Chen et al. 2022). Most of studies exploring these relationships have found that highly capitalized banks are more cost efficient than banks with low capitalization levels (Bitar et al. 2018; Fiordelisi et al. 2011; Sarmiento and Galán 2017). Sarmiento and Galán (2017) argued that this relation is explained by the agency problems between shareholders and managers. Shareholders of highly capitalized banks are expected to have stronger incentives to better control costs and capital allocation compared to those of banks with lower capitalization.

However, conflicting findings suggest that highly capitalized banks may take on more risk due to a moral hazard mechanism, which holds that increasing capital requirements constitute a means of reducing bank managers' perceptions of the risk of default and increase risk-taking (Delis et al. 2015; Jokipii and Milne 2011).

Finally, exposure to market risk is the risk of losses to the bank arising from movements in market prices because of changes in interest rates, foreign exchange rates and equity and commodity prices (Apostolik et al. 2012). We have measured the exposure to this risk as securities investments over total assets. Operating costs associated with securities investments are generally lower than those involved in monitoring and assessing loans did. However, higher holdings of securities also entail higher market risk exposure (Sarmiento and Galán 2014), so the influence on cost efficiency is not clear because it depends on different factors and contexts.

The size of a bank significantly affects its cost efficiency, with larger banks often demonstrating greater efficiency through economies of scale (S. Chen et al. 2020). Achieving economies of scale enables them to optimize operations, spread fixed costs and benefit from lower funding costs. Perceived as more stable, large banks can attract funds at a lower cost, aided by the 'too-big-to-fail' perception, making them more likely to receive government support in times of financial distress. Their size allows for substantial investments in technology and innovation, yielding efficiency gains and improved customer service.

However, the complex organizational structure of large banks may lead to higher managerial costs, potentially hindering efficiency (Krause et al. 2017). Additionally, increased size exposes banks to heightened regulatory scrutiny, emphasizing the critical importance of compliance and robust risk management practices for these institutions.

#### 2.2.3 | Environmental Characteristics

When examining environmental characteristics, our analysis encompasses two distinct sets of variables: those tailored to the banking industry and those specific to the country of operation. Within the banking sector, our focus extends to Market Concentration, Financial Depth and Non-performing Loans. On the broader economic landscape, influencing various sectors within the country, our variables include Strength of Legal Rights, GDP Growth, GDP per Capita, and Inflation Rate. This comprehensive approach allows us to capture the nuanced interplay between industry-specific dynamics and broader economic influences.

Market concentration significantly shapes banks' dynamics and strategies. Kozak and Wierzbowska (2021) reviewed the earlier research and found that, in the short term, banks with a substantial market share increase prices and generate higher profits, but in the long term, their improper loans monitoring and excessive operating costs lead to a drop in their efficiency and competitiveness. However, the efficient structure hypothesis (Demsetz 1973) states that under the pressure of market competition, more efficient firms acquire less efficient competitors and then, due to the use of economies of scale and scope they reduce operating costs. This process increases market concentration but also improves the efficiency of firms operating in it (Mateev et al. 2023). This is consistent with the relative market power paradigm, which predicts that larger firms, due to greater economies of scale and scope, have the capacity to decrease operating costs and to expand the diversification of their products, and hence increase the efficiency (Kozak and Wierzbowska 2021).

Financial Depth, measured by the ratio of domestic credit to private sector over GDP, is commonly used in the literature to control for the levels of financial development across countries. Higher prominence of banks in providing credit could imply a higher sophistication of the banking sector, while lower levels may also reflect the credit constraints faced by borrowers, thus likely generating competing impacts on the stability of banking markets (M. Chen et al. 2017b). Banks in countries with higher financial depth may employ more financial instruments to hedge their risk, which may reduce their cost of liabilities and hence enhance their efficiency (M. Chen et al. 2022). In consequence, a positive influence of this variable on cost efficiency is expected.

Non-performing loans (NPLs), calculated as the ratio of NPLs to the total loan portfolio, are a critical indicator of bank health and efficiency. This ratio, with a negative association to operating efficiency (Khan et al. 2020), plays a pivotal role in identifying asset quality issues, influencing the stability of a country's banking sector. Elevated NPL levels require increased monitoring efforts, incurring higher costs. Effectively managing NPLs is crucial for overall bank health necessitating proactive risk management and control measures.

In terms of country-specific variables, which consequently influence any economic sector in the country, the first variable is the Strength of Legal Rights. This index, developed by the World Bank, measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders, thereby facilitating lending. The index, ranging from 0 to 12, with higher scores indicating better-designed laws for expanding access to credit, is positively related to banking efficiency. The Strength of Legal Rights index plays a pivotal role in shaping the environment for banking operations, contributing to reduced risks and lower costs for banks. However, Kalyvas and Mamatzakis (2014) found that the strength of creditor rights is negatively related to cost efficiency, although this effect subdues during the crisis period (2008–2010).

Continuing with the country-specific variables, the second aspect is GDP Growth. The operational landscape of the banking sector is significantly shaped by GDP growth, influencing strategic decisions related to cost management, risk-taking and the pursuit of profitable ventures. Explored in the literature for its impact on risk-taking in the banking industry (Borauzima and Muller 2023; M. Chen et al. 2017b), economic growth is associated with reduced bank risk during expansions, where lending is less exposed to default (Borauzima and Muller 2023). However, in a favourable economic environment, banks pay less attention to cost control policies and are more likely to finance riskier transactions, which implies higher monitoring costs.

Moving on, the third factor is GDP per Capita. A country with a higher GDP per capita is anticipated to possess more advanced market regimes, potentially benefiting banking efficiency (Chen et al. 2022). GDP per Capita plays a pivotal role in shaping loan repayment dynamics and banking efficiency. Elevated income levels within a population enhance loan repayment capacity and resilience in economic downturns, subsequently influencing the overall risk profile of banks and their efficiency in cost management.

Finally, the inflation rate, much like GDP growth, has been explored in the literature for its influence on risk-taking in the banking industry. A higher inflation rate can escalate borrowing costs, increasing a bank's risk exposure (Borauzima and Muller 2023). This indicator provides insight into policy adjustments, with a higher value indicative of a contractionary policy and a lower value suggestive of an expansionary policy (M. Chen et al. 2017b). The inflation rate introduces complexities into the operational landscape of banks, necessitating adaptive strategies to navigate its effects. Banks often prioritize cost management in response to inflation, recognizing its potential to erode the value of invested funds. While inflation poses challenges, it also presents opportunities for banks to demonstrate resilience and strategic flexibility. An understanding of the interplay between inflation and cost management is essential for banks to thrive in dynamic economic environments.

Table 2 summarizes all explanatory variables included in the efficiency model, organized according to the type of efficiency they influence (intrinsic or extrinsic). For each variable, the

**TABLE 2** | Determinants of intrinsic and extrinsic efficiencies: definitions, expected effects and data sources.

| | Explicative variable | Description | Expected sign effect | Source |
|---|---|---|---|---|
| Intrinsic efficiency | Credit Risk | Loan Loss Reserves/Gross Loans | — | Orbis bank Focus and Orbis databases |
| | Liquidity Risk | Liquid Assets/Total Assets | +/− | |
| | Equity Risk | Equity/Total Assets | +/− | |
| | Market Risk | Securities/Total Assets | +/− | |
| | Size | Total Assets | + | |
| Extrinsic efficiency | Market concentration | Assets of five largest banks as a share of total commercial banking assets | +/− | World Bank: World Development Indicators (WDI) |
| | Financial Depth | Domestic credit to private sector/GDP | + | |
| | Non-performing loans | Nonperforming loans divided by the total value of the loan portfolio | — | |
| | Strength of legal rights | Degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit | +/− | |
| | GDP Growth | Annual percentage growth rate of GDP at market prices based on constant local currency | +/− | |
| | GDP per capita | Gross domestic product divided by midyear population | + | |
| | Inflation rate | Annual percentage change in the cost to the average consumer of acquiring a basket of goods and services | +/− | |

table provides a description, the expected effect on cost efficiency and the corresponding data source.

## 3 | Methodology

In this section, we outline the methodology employed to assess cost efficiency in the banking sector. Our model utilizes a stochastic Cobb–Douglas frontier model[2] where the cost efficiency is split into two components: one dependent on exposure to risks and size, which we name as intrinsic efficiency, and the other associated with the operational environment, which we name as extrinsic efficiency.

### 3.1 | Model Specification

Let $C = \log(\text{Cost})$ be the logarithm of the cost. As commented in Section 2.2.1, we follow an approach based on the modified version of the value-added approach. Two input prices, $X_1 = \log(\text{Price of Funds})$ and $X_2 = \log(\text{Price of Capital})$, are introduced to the model, reflecting the logarithm of the price of capital and the price of funds, respectively.

To improve interpretability and avoid potential issues related to the functional form of the cost function, we normalize the model by the price of capital and assume constant returns to scale. This transformation simplifies the interpretation of coefficients in terms of relative prices and is consistent with common practices in the literature, especially when estimating cost functions in the presence of price effects that may otherwise bias the estimation (Doan et al. 2018; Tan and Floros 2018).

In this way the dependent variable is $c = \log(\text{Cost/Price of Capital})$ and the input variable $X_1 = \log(\text{Price of Funds/Price of Capital})$.

Four output variables, $Y_1 = \log(\text{Deposits})$, $Y_2 = \log(\text{Loans})$, $Y_3 = \log(\text{Other Earning Assets})$, $Y_4 = \log(\text{Off-Balance sheet items})$, represent various aspects, including the logarithm of deposits, loans, other earning assets and off-balance sheet items.

Efficiency determinants encompass both exposure to risks, size and external factors. Credit risk ($Z_1$), liquidity risk ($Z_2$), equity risk ($Z_3$) and market risk ($Z_4$) constitute the risk-related determinants. Bank-specific characteristic includes the logarithm of assets ($Z_5$). Country/sector-level characteristics comprise market concentration ($W_1$), financial depth ($W_2$), non-performing loans ($W_3$), strength of legal rights ($W_4$), GDP growth ($W_5$), GDP per capita ($W_6$) and inflation rate ($W_7$). All the independent variables were centred.

In the Supporting Information (section SM1), a descriptive analysis of all these variables is provided. Specifically, it can be observed that there are no significant issues with multicollinearity among the independent variables in Equations (1)–(3).

The data set consists of an unbalanced panel of $N = 1107$ banks from 28 European countries, listed in Table 1, observed over $T$ time periods, spanning from 2004 to 2020:

$$\{(c_{i,t}, \mathbf{y}_{i,t} = (y_{1it}, y_{2it}, y_{3it}, y_{4it})'; x_{i,t} = x_{1it}; z_{i,t} = (z_{1it}, z_{2it}, z_{3it}, z_{4it}, z_{5it}, z_{6it})'; \mathbf{w_{c(i),t}} = (w_{1c(i)t}, w_{2c(i)t}, w_{3c(i)t}, w_{4c(i)t}, w_{5c(i)t}, w_{6c(i)t}, w_{7c(i)t})'; t \in T\text{i}; i = 1, \ldots, N\} \text{ with } \mathrm{T_i} \subseteq \{1, \ldots, T\} \text{ and } c(i) \in \{AUT, \ldots, UKG\}$$

where each bank $i$ is associated with a country code $c(i)$.

This framework acknowledges the inherent diversity in observation durations across banks, as some have longer observation periods than others, reflecting the heterogeneity of the data set in terms of countries and years while also minimizing survival bias.

If $0 \leq \mathrm{TE}_{\mathrm{int},i,t}, \mathrm{TE}_{\mathrm{ext},c(i),t} \leq 1$ denote the technical intrinsic and extrinsic efficiencies of bank $i$ at time $t$, respectively, the general form of the stochastic frontier model considered in the paper is given by

$$c_{i,t} = \alpha_0 + \alpha_1 x_{i,t} + \sum_{j=1}^{4} \beta_j y_{j,i,t} + \nu_{i,t} - \log(\mathrm{TE}_{\mathrm{int},i,t}) - \log(\mathrm{TE}_{\mathrm{ext},c(i),t}), \tag{1}$$

$$\nu_{i,t} \sim N\left(0, \sigma_\nu^2\right); \; t \in Ti; \; i = 1, \ldots, N, \tag{2}$$

where $\alpha_0 + \alpha_1 x_{i,t} + \sum_{j=1}^{4} \beta_j y_{j,i,t}$ is the frontier function of the model, which determines the minimum total cost that can be achieved using the input $x_{i,t}$ and the outputs $y_{i,t}$, and $\nu_{i,t}$ is an idiosyncratic error term.

The intrinsic and extrinsic efficiency components are reparametrized using a logit transformation to facilitate their mathematical handling. For both components, we specify a dynamic regression model. Intrinsic efficiency is explained by bank-specific characteristics (such as size and various types of risk exposures), while extrinsic efficiency is modelled using country- and sector-level factors described earlier. This structure allows us to capture the influence of both internal management features and the broader banking environment on cost efficiency. The expressions of these regressions are given by[3]:

$$s_{\mathrm{int},i,t} = \log\left(\frac{\mathrm{TE}_{\mathrm{int},i,t}}{1 - \mathrm{TE}_{\mathrm{int},i,t}}\right) = \sum_{k=1}^{5} \delta_{\mathrm{int},k} z_{k,i,t} + \xi_{\mathrm{int},i,t} \text{ with } \xi_{\mathrm{int},i,t} \sim N\left(0, \sigma^2_{\xi_{\mathrm{int}},c(i)}\right); \; t \in T_i; \; i = 1, \ldots, N, \tag{3}$$

$$s_{\mathrm{ext},c(i),t} = \log\left(\frac{\mathrm{TE}_{\mathrm{ext},c(i),t}}{1 - \mathrm{TE}_{\mathrm{ext},c(i),t}}\right) = \sum_{\ell=1}^{7} \delta_{\mathrm{ext},\ell} w_{\ell,c(i),t} + \xi_{\mathrm{ext},c(i),t} \text{ with } \xi_{\mathrm{ext},c(i),t} \sim N\left(0, \sigma^2_{\xi_{\mathrm{ext}},c(i)}\right) \tag{4}$$

$$t \in \{t_{\min,c(i)}, \ldots, t_{\max,c(i)}\} \text{ where } t_{\min,c(i)} = \min_{j:c(j)=c(i)} \bigcup_j T_j, \; t_{\max,c(i)} = \max_{j:c(j)=c(i)} \bigcup_j T_j.$$

The total cost efficiency is equal to $\mathrm{TE}_{\mathrm{total},i,t} = \sqrt{\mathrm{TE}_{\mathrm{int},i,t}\mathrm{TE}_{\mathrm{ext},c(i),t}}$. Finally, $\mathrm{PE}_{\mathrm{int},i,t} = 100\frac{\log(\mathrm{TE}_{\mathrm{int},i,t})}{\log(\mathrm{TE}_{\mathrm{int},i,t}) + \log(\mathrm{TE}_{\mathrm{ext},c(i),t})}$ is the percentage of the log-efficiency explained by the intrinsic log-efficiency.

In the regression models (3) and (4), we exclude the intercept terms to avoid identifiability issues associated with the intrinsic and extrinsic efficiency components $\mathrm{TE}_{\mathrm{int}}$ and $\mathrm{TE}_{\mathrm{ext}}$ in Equation (1).[4] Specifically, this implies that the conditional medians $\mathrm{Med}(s_{\mathrm{int}}|Z = 0) = \mathrm{Med}(s_{\mathrm{ext}}|W = 0)$ are both equal to 0. In other words, a bank with average characteristics in terms of risk and size, operating in a country with average environmental conditions, is expected to have intrinsic and extrinsic efficiencies of approximately 0.5. This benchmark value serves as a useful reference for evaluating the relative importance of each efficiency component.

This modelling strategy enables us to capture the multidimensional nature of bank efficiency by explicitly accounting for both institution-specific d\rivers and broader environmental influences.

### 3.2 | Bayesian Inference

Given that we adopt a Bayesian approach, we have to specify a prior distribution on the parameters of the model. To that aim, we use standard fairly non-informative distributions given by:

$$(\alpha_0 \;\; \alpha_1 \;\; \beta_1 \;\; \beta_2 \;\; \beta_3 \;\; \beta_4)' \sim N_6(0, 1000 I_6); \quad \tau_\nu = \frac{1}{\sigma_\nu^2} \sim \mathrm{Gamma}(0.001, 0.001),$$

$$(\delta_{\mathrm{int},1} \;\; \delta_{\mathrm{int},2} \;\; \delta_{\mathrm{int},3} \;\; \delta_{\mathrm{int},4} \;\; \delta_{\mathrm{int},5})' \sim N_5(0, 1000 I_5); \quad \tau_{\xi_{\mathrm{int}},c} = \frac{1}{\sigma^2_{\xi_{\mathrm{int}},c}} \sim \mathrm{Gamma}(0.01, 0.01);$$

$c \in \{AUT, \ldots, UKG\}$

$$(\delta_{\mathrm{ext},1} \;\; \delta_{\mathrm{ext},2} \;\; \delta_{\mathrm{ext},3} \;\; \delta_{\mathrm{ext},4} \;\; \delta_{\mathrm{ext},5} \;\; \delta_{\mathrm{ext},6} \;\; \delta_{\mathrm{ext},7})' \sim N_7(0, 1000 I_7)$$

$$\tau_{\xi_{\mathrm{ext}},c} = \frac{1}{\sigma^2_{\xi_{\mathrm{ext}},c}} \sim \mathrm{Gamma}(0.01, 0.01); \; c \in \{AUT, \ldots, UKG\} \tag{5}$$

all of them, mutually independents and independents of (1)–(4).

The inference about parameters was carried out from their posterior distribution, which is calculated using the Bayes theorem. Given that this distribution is not tractable analytically, we use MCMC methods and, in particular, Gibbs sampling with Hastings-Metropolis steps implemented using library *nimble*

0.10.1 (De Valpine et al. 2017). For each model considered, we ran three chains in parallel with a burn-in number of iterations equal to 10,000 and, posteriorly, 15,000 iterations where we take one each 50 steps. Convergence diagnostics are presented in Section SM6 of the Supporting Information, where no significant convergence issues are observed. The final posterior sample size is 900, ensuring sufficient information for reliable inference.

### 3.3 | Comparison of Models

One of the advantages of Bayesian inference is its ability to assess model fit to the data, allowing for the selection of the most appropriate specification. In our case, we use the WAIC (Watanabe-Akaike Information Criterion), a fully Bayesian generalization of the classical AIC introduced by Akaike (1973) and developed by Watanabe and Opper (2010). WAIC measures the out-sampling predictive capacity of the model in such a way that, the smallest its value is, the greater is its out-sampling predictive capacity.

Additionally, to assess the model's goodness of fit, we compute several diagnostic metrics: the Mean Absolute Deviation (MAD); the empirical coverage (COV) of the 95% posterior credibility interval for $C = \log(\text{Cost})$, constructed from the 2.5% and 97.5% quantiles of its posterior predictive distribution; and the squared correlation coefficient ($R^2$) between the observed values ($C$) and their predicted counterparts ($C_{pred}$), where predictions are based on the posterior median of $C$.

**TABLE 3** | Summary of model performances.

| | M1 | M2 | M3 | M4 |
|---|---|---|---|---|
| COV | 0.9445 | 0.9471 | 0.9483 | 0.9452 |
| MAD | 0.5114 | 0.4888 | 0.4983 | 0.4920 |
| $R^2$ | 0.9227 | 0.9256 | 0.9356 | 0.9252 |
| WAIC | 8785.24 | 8278-89 | 20736.86 | **7101.12** |

*Note:* This table compares four models: Model M1 adopts a constant efficiency level; M2 includes only the intrinsic efficiency component; M3 includes only the extrinsic efficiency component; and M4 includes both intrinsic and extrinsic efficiency components. In bold signalled the best model.

## 4 | Results

### 4.1 | Estimation and Model Selection

This general model lets us explore a wide range of configurations about the evolution of efficiencies. In addition, the Bayesian comparison of models approach allows us to assess a broad array of scenarios and gain a better understanding of their impact on cost efficiency.

Table 3 provides a comparative analysis of models, which made different assumptions about the general model (1)–(4). The first model M1 assumes that $\delta_{\text{int},i} = 0$; $i = 1,\dots,5$; $\delta_{\text{ext},j} = 0$; $\text{i} = 1,\dots,7$. This specification implies that bank efficiencies do not depend on risk exposure, size, or environmental characteristics. The second model M2 assumes that $\delta_{\text{ext},j} = 0$; $i = 1,\dots,7$, that is, that there is no extrinsic component in the total efficiency, in such a way that $\text{TE}_{\text{ext},i,t} = 1\ \forall i,t$. The third model M3 assumes that $\delta_{\text{int},j} = 0$; $i = 1,\dots,5$, that is, that there is no intrinsic component in the total efficiencies in such a way that $\text{TE}_{\text{int},i,t} = 1$ $\forall_{i,t}$. Finally, the model M4 is the general model (1)–(4).

The analysis reveals that the best model in terms of the WAIC criterion is the general model M4 that minimizes it. In addition, the goodness of fit to data of this model is adequate: the empirical coverage of the posterior 95% credibility interval is 94.52% very similar to the 95% credibility level, the $R^2$ criterion is equal to 0.9252 and the MAD value (0.4920) is very similar to its best value (0.4888). Finally, Figure 1 compares the predicted values of log(Cost) with the observed values. The results show a close alignment between the two, with most observed values falling within the bounds of the 95% credible intervals.

Next, we present the estimations of the parameters from the model M4. Concretely we show, for each parameter, its

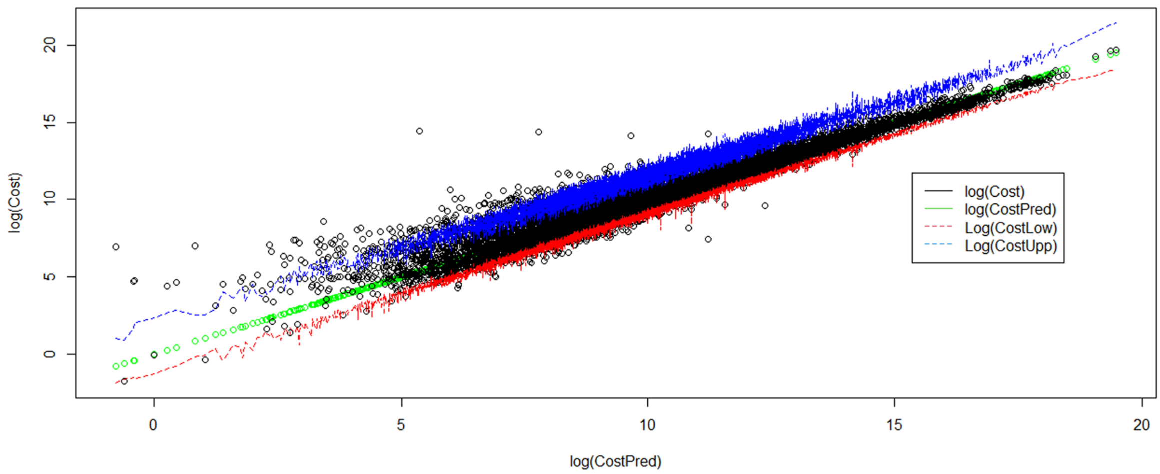


**FIGURE 1** | Scatter plot of predicted versus observed values of log(Cost) with 95% credible intervals for model M4. Each point represents a bank-year observation. The predicted values (log(CostPred)) correspond to the posterior median of the predictive distribution, while the lower (log (CostLow)) and upper (log(CostUpp)) bounds represent the 2.5% and 97.5% quantiles of that distribution, respectively. [Color figure can be viewed at wileyonlinelibrary.com]

posterior median and the limits of its 95% credibility interval built from its posterior 2.5% and 97.5% posterior quantiles. In addition, we signal in italics (bold) the coefficients 95% statistically significant positive (negative).

**TABLE 4** | Frontier model coefficients estimations (see Expressions (1) and (2)).

| Variable | Median | 95% Low | 95% Upp |
|---|---|---|---|
| Constant ($\alpha_0$) | *8.7027* | *8.6757* | *8.7294* |
| LPFund ($\alpha_1$) | *0.8974* | *0.8900* | *0.9038* |
| LDeposits ($\beta_1$) | *1.0000* | *0.9799* | *1.0197* |
| LLoans ($\beta_2$) | *0.0177* | *0.0062* | *0.0305* |
| LOtherEarnAssets ($\beta_3$) | **−0.0184** | **−0.0286** | **−0.0069** |
| LOffBalance ($\beta_4$) | *0.1711* | *0.1459* | *0.1967* |
| $\tau_v$ | *15.4371* | *14.2320* | *16.5182* |

*Note:* In italics (bold) signalled the coefficients 95% statistically significant positive (negative). This table reports the posterior median (Median) of each estimated coefficient, along with the lower (95% Low) and upper (95% Upp) limits of the 95% credibility interval, constructed from the 2.5% and 97.5% posterior quantiles. Note that $\tau_v = \frac{1}{\sigma_v^2}$

We start with the efficient frontier model in Table 4.

As expected, the coefficients for the Price of Funds, Loans, Deposits and Off-Balance Sheet items are significantly positive. In contrast, total cost is negatively associated with Other Earning Assets, reflecting their relatively lower cost for banks compared to other outputs. Among all factors, Deposits and the Price of Funds exhibit the largest impacts on the cost frontier, with estimated elasticities of 1.0000 and 0.8974, respectively. The latter implies a residual elasticity of 0.1026 with respect to the Price of Capital, given the normalization used in the model.

Table 5 presents the estimation results for the intrinsic efficiency component, highlighting the effects of bank-specific characteristics related to risk exposure and size.

As expected, the impact of risk exposure variables on banking efficiency is notable, with all exhibiting statistically significant influence. Specifically, higher risk is associated with lower efficiency, which is logically sound. Berger and DeYoung (1997) previously justified this negative relationship in terms of the additional costs involved in monitoring, negotiating possible workout arrangements, disposing of collateral in the event of defaults, defending the bank's safety to the market and

**TABLE 5** | Estimation of the intrinsic efficiency parameters (see Expression (3)).

| Variable/Parameter | Median | 95% Low | 95% Upp | Parameter | Median | 95% Low | 95% Upp |
|---|---|---|---|---|---|---|---|
| Credit risk ($\delta_{\text{int},1}$) | **−1.1872** | **−1.5007** | **−0.8218** | $\tau_{\xi_{\text{int}},lat}$ | *2.1389* | *1.6043* | *2.7 723* |
| Liquidity risk ($\delta_{\text{int},2}$) | **−1.5022** | **−1.7492** | **−1.2387** | $\tau_{\xi_{\text{int}},lit}$ | *30.0668* | *8.8901* | *203.9412* |
| Equity risk ($\delta_{\text{int},3}$) | **−2.3800** | **−2.6419** | **−2.1199** | $\tau_{\xi_{\text{int}},lux}$ | *0.7360* | *0.6153* | *0.8683* |
| Market risk ($\delta_{\text{int},4}$) | **−0.1247** | **−0.2632** | **0.0265** | $\tau_{\xi_{\text{int}},mal}$ | *0.7115* | *0.4498* | *1.1397* |
| LAssets ($\delta_{\text{int},5}$) | *0.1508* | *0.1296* | *0.1730* | $\tau_{\xi_{\text{int}},nth}$ | *0.8422* | *0.6179* | *1.0972* |
| $\tau_{\xi_{\text{int}},aut}$ | *0.6026* | *0.5065* | *0.7085* | $\tau_{\xi_{\text{int}},pol}$ | *3.6550* | *2.7276* | *5.0803* |
| $\tau_{\xi_{\text{int}},bel}$ | *0.5216* | *0.3911* | *0.6673* | $\tau_{\xi_{\text{int}},por}$ | *1.5605* | *1.1355* | *2.1547* |
| $\tau_{\xi_{\text{int}},bul}$ | *4.1553* | *2.9865* | *5.9824* | $\tau_{\xi_{\text{int}},rom}$ | *61.8022* | *19.1875* | *247.7221* |
| $\tau_{\xi_{\text{int}},cro}$ | *12.7498* | *8.3096* | *22.7552* | $\tau_{\xi_{\text{int}},slk}$ | *1.3116* | *0.9263* | *1.8112* |
| $\tau_{\xi_{\text{int}},cyp}$ | *0.4927* | *0.3476* | *0.6614* | $\tau_{\xi_{\text{int}},slv}$ | *5.5979* | *3.5464* | *9.4834* |
| $\tau_{\xi_{\text{int}},cze}$ | *0.6372* | *0.4764* | *0.8440* | $\tau_{\xi_{\text{int}},spa}$ | *0.7021* | *0.5819* | *0.8365* |
| $\tau_{\xi_{\text{int}},dnk}$ | *1.0548* | *0.8867* | *1.2694* | $\tau_{\xi_{\text{int}},swe}$ | *0.8513* | *0.6731* | *1.0751* |
| $\tau_{\xi_{\text{int}},est}$ | *32.7728* | *8.5384* | *188.3884* | $\tau_{\xi_{\text{int}},ukg}$ | *1.2001* | *1.0472* | *1.3629* |
| $\tau_{\xi_{\text{int}},fin}$ | *0.8100* | *0.5675* | *1.1608* | | | | |
| $\tau_{\xi_{\text{int}},fra}$ | *0.7718* | *0.6954* | *0.8611* | | | | |
| $\tau_{\xi_{\text{int}},ger}$ | *0.5270* | *0.4646* | *0.5962* | | | | |
| $\tau_{\xi_{\text{int}},gre}$ | *29.4412* | *9.0547* | *176.5035* | | | | |
| $\tau_{\xi_{\text{int}},hun}$ | *1.9913* | *1.5321* | *2.6164* | | | | |
| $\tau_{\xi_{\text{int}},ire}$ | *1.0424* | *0.6517* | *1.6053* | | | | |
| $\tau_{\xi_{\text{int}},ita}$ | *0.9233* | *0.8061* | *1.0364* | | | | |

*Note:* In italics (bold) signalled the coefficients 95% statistically significant positive (negative). This table reports the posterior median (Median) of each estimated coefficient, along with the lower (95% Low) and upper (95% Upp) limits of the 95% credibility interval, constructed from the 2.5% and 97.5% posterior quantiles. Note that $\tau_{\text{int},c} = \frac{1}{\sigma^2_{\text{int},c}}$ for $c \in \{aut, \ldots, ukg\}$.

supervisor, and taking additional precautions to ensure the quality of other loans. Since then, many papers have identified the same relationship (Fries and Taci 2005; Kirkpatrick et al. 2008; Sarmiento and Galán 2017). Similarly, a higher level of market risk is slightly associated with lower efficiency. Although investing in securities is cheaper than monitoring and assessing loans, higher market risk negatively affects cost efficiency due to increased exposure to market risk.

In contrast, concerning liquidity and capitalization risks, higher risk exposure is linked to greater efficiency (higher capitalization and liquidity are negatively associated with efficiency). Regarding the negative effect of capitalization, this result is supported by the idea that highly capitalized banks may take on more risk due to a moral hazard mechanism, which holds that increasing capital requirements constitute a means of reducing bank managers' perceptions of the risk of default and increase risk-taking (Delis et al. 2015; Jokipii and Milne 2011). Some previous studies have also found this inverse relationship (Altunbas et al. 2007; Sun and Chang 2011; Doan et al. 2018). Regarding the negative effect observed for the liquidity ratio, this result suggests that to maintain high liquidity positions banks incur higher costs to attract more funds. This negative association is in line with Sakouvogui and Shaik (2020) for US commercial banks or Dong et al. (2017) for Chinese banks.

These last results are interesting as in the aftermath of the global crisis prudential regulators applied stricter regulations, especially in terms of capitalization and liquidity, which according to the results might be contributing to a decrease in cost efficiency. It should be noted that among all the risks, capitalization risk has the most pronounced impact, followed by liquidity risk.

In addition, a positive effect of bank size is observed, meaning larger banks tend to be more efficient. This result was expected because larger banks often demonstrate greater efficiency through economies of scale. In addition, this relationship has been usually reported in the literature as evidence of the too-big-to-fail dilemma where larger banks take advantage of their size to obtain funds at lower cost (Santos 2014). Finally, it can be noticed that the existence of a significant heteroscedasticity in regression models (2) where the larger precisions $\tau_{\xi_{\text{int}},c}$ tend to correspond to the Eastern countries and Greece, where the number of banks is lower and with a more homogeneous behaviour. On the contrary, the lower precisions tend to be associated to the Western countries where the number of banks is larger and with a more heterogeneous behaviour.

Table 6 provides a comprehensive overview of the environmental variables influencing extrinsic banking efficiency.

Notably, two covariates were identified as having a significantly negative impact: Market Concentration and Strength of Legal Rights. Conversely, two other covariates were identified as having a significantly positive impact: Financial Depth and Inflation Rate. According to Kozak and Wierzebowska (2021), the adverse relationship between market concentration and banking efficiency is due to the fact that, in the long term, banks with a substantial market share experience increasing costs as a result of improper loan monitoring and excessive operating costs. Regarding the negative effect of stronger legal rights, it should be noted that they encourage more lending. This means that banks need more resources for this purpose, which increases competition among them to attract funds and raises costs. Previously, Kalyvas and Mamatzakis (2014) also found this negative association. In contrast, the expected positive effect of financial depth is associated with the use of more financial instruments to hedge banking risk in countries with higher financial depth (M. Chen et al. 2022). Finally, the significant positive effect of the inflation rate on efficiency suggests that, when faced with rising costs in an inflationary environment, banks manage their resources more efficiently to minimize the impact on total costs. This relationship has been reported previously by Tan and Floros (2018).

Moreover, it is crucial to highlight that the error terms in our model tend to exhibit high precision, suggesting that extrinsic efficiencies evolve smoothly over time and across countries. The $\tau_{\xi_{ext},c}$ values vary significantly between countries, indicating heterogeneity. It is not surprising because in countries with steady economic and regulatory environments, banks tend to maintain consistent efficiency levels. A stable economic setting, predictable GDP growth, controlled interest rates and clear banking regulations allow banks to optimize operations and sustain efficiency. Political stability and a well-developed financial infrastructure further support this.

### 4.2 | Graphical Analysis of Global Temporal Evolution

This section aims to leverage the estimations presented in the previous tables for a graphical analysis, providing visual insights into the temporal evolution of the considered variables. Visual representations allow exploring the influence of the variables on banking efficiency over time, offering a concise and illuminating perspective. This graphical representation provides a dynamic visualization of how banking efficiency responds to changing circumstances, helping to identify trends, turning points and potential areas of concern or improvement. By examining the temporal dimension across nations, stakeholders can gain insights into the effectiveness of policy changes, economic shifts and other external factors on the banking sector's efficiency landscape. This global analysis complements the other approaches, offering a time-centric view that aids in understanding the resilience and adaptability of banking systems across diverse environments.

Thus, Figure 2 depicts, above, the estimation of the annual evolution, for each country $c \in \{AUT, ..., UKG\}$, of the median of the efficiencies of its banks explained by intrinsic factors, $\text{median}_{i:c(i)=c}\{\text{TE}_{\text{int},i,t}\}$, for $t = t_{\text{min},c}, ..., t_{\text{max},c}$, where the efficiency of each bank was estimated by its posterior median. Below and for each country, it depicts the boxplots of these values to make the comparison of its efficiency values easier. In general, there are significant differences on average efficiency levels between countries, and most of the have shown a slight negative trend over time.

The results show that, on average, banks in countries such as Belgium, the Netherlands and Ireland tend to have higher

TABLE 6 | Estimation of the extrinsic efficiency parameters (see Expression (4)).

| Variable/Parameter | Median | 95% low | 95% Upp | Parameter | Median | 95% low | 95% Upp |
|---|---|---|---|---|---|---|---|
| Market_Conc ($\delta_{\text{ext},1}$) | **−0.0099** | **−0.0136** | **−0.0054** | $\tau_{\xi_{\text{ext}},lat}$ | 2.9032 | 1.1776 | 6.3456 |
| Financial_Depth ($\delta_{\text{ext},2}$) | *0.0030* | *0.0018* | *0.0043* | $\tau_{\xi_{\text{ext}},lit}$ | 13.6627 | 3.7984 | 69.3455 |
| LNonPerform_Loans ($\delta_{\text{ext},3}$) | −0.0160 | −0.0664 | 0.0375 | $\tau_{\xi_{\text{ext}},lux}$ | 40.0893 | 6.5313 | 176.4427 |
| StrengthLegal_Rights ($\delta_{\text{ext},4}$) | **−0.0527** | **−0.0814** | **−0.0254** | $\tau_{\xi_{\text{ext}},mal}$ | 5.1903 | 0.9932 | 96.7325 |
| GDP_Growth ($\delta_{\text{ext},5}$) | 0.0048 | −0.0074 | 0.0162 | $\tau_{\xi_{\text{ext}},nth}$ | 2.7351 | 0.9027 | 8.6060 |
| LGDP_PC ($\delta_{\text{ext},6}$) | 0.0184 | −0.0389 | 0.0736 | $\tau_{\xi_{\text{ext}},pol}$ | 5.7141 | 2.3165 | 11.9742 |
| Inflation_Rate ($\delta_{\text{ext},7}$) | *0.0943* | *0.0681* | *0.1216* | $\tau_{\xi_{\text{ext}},por}$ | 10.5849 | *3.1466* | 59.7089 |
| $\tau_{\xi_{\text{ext}},aut}$ | 28.3837 | 7.6762 | 145.5592 | $\tau_{\xi_{\text{ext}},rom}$ | 5.2872 | 2.2066 | 11.5788 |
| $\tau_{\xi_{\text{ext}},bel}$ | 11.9413 | 3.6476 | 55.6221 | $\tau_{\xi_{\text{ext}},slk}$ | 55.6109 | 10.6972 | 254.0605 |
| $\tau_{\xi_{\text{ext}},bul}$ | 1.4860 | 0.6309 | 2.8060 | $\tau_{\xi_{\text{ext}},slv}$ | 1.4495 | 0.6532 | 2.8802 |
| $\tau_{\xi_{\text{ext}},cro}$ | 2.2826 | 0.9612 | 4.7645 | $\tau_{\xi_{\text{ext}},spa}$ | 3.5073 | 1.6299 | 7.1369 |
| $\tau_{\xi_{\text{ext}},cyp}$ | 58.0760 | 13.4215 | 274.6482 | $\tau_{\xi_{\text{ext}},swe}$ | 5.0925 | 1.9889 | 12.9456 |
| $\tau_{\xi_{\text{ext}},cze}$ | 23.0929 | 5.3914 | 143.1308 | $\tau_{\xi_{\text{ext}},ukg}$ | 8.6474 | 3.5147 | 19.3172 |
| $\tau_{\xi_{\text{ext}},dnk}$ | 1.2140 | 0.5500 | 2.3223 | | | | |
| $\tau_{\xi_{\text{ext}},est}$ | 4.0964 | 1.5220 | 11.0158 | | | | |
| $\tau_{\xi_{\text{ext}},fin}$ | 2.2730 | 0.8867 | 4.7764 | | | | |
| $\tau_{\xi_{\text{ext}},fra}$ | 6.6349 | 2.9337 | 13.8361 | | | | |
| $\tau_{\xi_{\text{ext}},ger}$ | 7.0723 | 2.6458 | 17.5778 | | | | |
| $\tau_{\xi_{\text{ext}},gre}$ | 8.4909 | 3.3456 | 23.8914 | | | | |
| $\tau_{\xi_{\text{ext}},hun}$ | 2.8477 | 1.2346 | 5.6756 | | | | |
| $\tau_{\xi_{\text{ext}},ire}$ | 1.6138 | 0.4983 | 5.3185 | | | | |
| $\tau_{\xi_{\text{ext}},ita}$ | 1.3310 | 0.5697 | 2.6797 | | | | |

*Note:* In italics (bold) signalled the coefficients 95% statistically significant positive (negative). This table reports the posterior median (Median) of each estimated coefficient, along with the lower (95% Low) and upper (95% Upp) limits of the 95% credibility interval, constructed from the 2.5% and 97.5% posterior quantiles. Note that for $\tau_{\text{ext},c} = \frac{1}{\sigma^2_{\text{ext},c}} c \in aut, \ldots, ukg$.

intrinsic efficiency. Conversely, efficiencies explained by intrinsic factors tend to be relatively lower in countries such as Croatia, Bulgaria, Denmark and Sweden. Furthermore, the decline in efficiency levels in Cyprus, Denmark and Italy towards the end of the period is particularly noteworthy.

Figure 3 shows above and for each county $c \in \{AUT, \ldots, UKG\}$ the annual evolution of the extrinsic efficiencies $\{\text{TE}_{\text{ext},c,t};\ \text{for}\ t = t_{\min,c}, \ldots, t_{\max,c}\}$ estimated by their posterior medians, and below the corresponding boxplots. As can be seen, the efficiency has worsened over the years in almost all countries, though not equally across the board. Notably, this deterioration in extrinsic efficiency has been observed in almost all countries since 2012, with the exception of Luxembourg, where it remains high. It should be noted that, in response to the international financial crisis, national and European authorities in many countries promoted mergers and acquisitions to strengthen national banking sectors. This process led to increased bank concentration, which, as discussed above, has a significant negative impact on cost efficiency. Furthermore, the results suggest that the improvement in the economic environment after the financial crisis caused financial institutions to relax their cost control, thereby contributing to a further deterioration in cost efficiency levels.

Throughout the period, Luxembourg and the Netherlands were the two countries with the highest levels of extrinsic efficiency. By contrast, countries with lower levels of efficiency included Latvia, Denmark, Estonia and Italy. The reduction in efficiency caused by extrinsic factors in Denmark is especially notable. In this case, it should be noted that it was the first country in the last decade to introduce negative interest rates in 2012 to discourage investors from buying a strong Danish krone. Denmark's National bank applied this policy to maintain the exchange rate with the euro within the agreed margins and support the country's exports. The negative rates were extended until 2022, resulting in a new financial framework that Danish banks had to adapt to.

Figures 2 and 3 suggest that banks have room for improvement and can recover previous efficiencies by improving their internal risk management and size, as well as by improving their response to changes in environmental conditions.

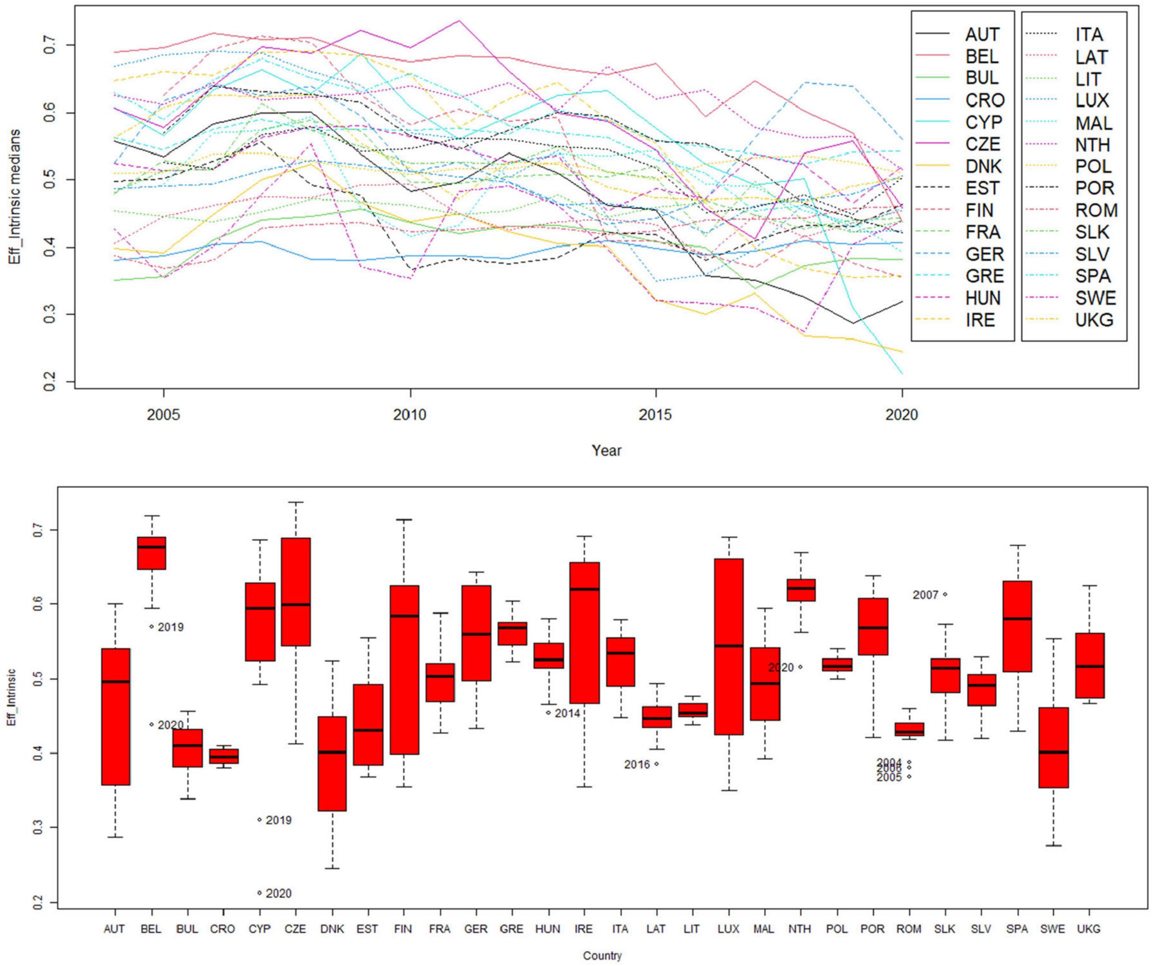


**FIGURE 2** | Evolution and distribution of intrinsic efficiency across countries estimated by Model M4. Top: Estimated annual evolution of the median intrinsic efficiency for each country, over time. Bottom: Boxplots summarizing the distribution of median intrinsic efficiencies for each country. [Color figure can be viewed at wileyonlinelibrary.com]

Figure 4 shows, above and for each country $c \in \{AUT, \dots, UKG\}$, the estimated annual evolution of the median of the total efficiencies of its banks, $\text{median}_{i:c(i)=c}\{\text{TE}_{\text{total},i,t}\}$, for $t = t_{\min,c},\dots,t_{\max,c}$, estimated by their posterior medians, and below, their corresponding boxplots.

The results presented in this Figure 4 are direct consequence of the intrinsic efficiencies (Figure 2) and extrinsic efficiencies (Figure 3) found for each bank/country. As can be seen, the average total efficiency of banks has declined gradually in most countries, primarily due to a slight deterioration in intrinsic efficiency and, more importantly, a sharp decline in extrinsic efficiency. Throughout this period, banks in countries such as the Netherlands and Ireland have demonstrated greater total efficiency. This is due to greater intrinsic efficiency in Ireland and greater extrinsic efficiency in the Netherlands. Banks in countries such as Belgium, Luxembourg and Portugal have also performed well. In contrast, the banks in Latvia, Sweden, Denmark and Estonia are the least efficient. This is because they have low levels of both intrinsic and extrinsic efficiency. This means their low efficiency levels are a consequence of their internal risk management, size and the environment in which they operate.

In light of our decomposition of total efficiency into its intrinsic and extrinsic components, Figure 5 depicts, for each country $c \in \{AUT, \dots, UKG\}$, the annual evolution of the median of the percentage of total efficiency ascribed to the intrinsic efficiencies of their banks ($\text{median}_{i:c(i)=c}\{\text{PE}_{\text{int},i,t}\}$ for $t = t_{\min,c},\dots,t_{\max,c}$) estimated by their posterior medians (above) and their corresponding boxplots (below).

This visual representation aims to provide a nuanced understanding of the factors contributing to inefficiency by offering insights into the relative impact of internal banking attributes on overall performance. Interestingly, the importance of intrinsic factors in explaining total inefficiency has varied greatly from one country to country and over time. In some countries, such as Croatia, Bulgaria, Romania and Luxembourg, the intrinsic factors of banks explain most of their inefficiency. In contrast, the majority of inefficiency in other countries, such as Belgium, Italy, Finland, the Czech Republic and Spain, is attributed to environmental conditions. However, in most countries, inefficiency is explained by intrinsic and extrinsic factors to a similar extent.

It is also noteworthy that certain countries have undergone significant changes during this period. For instance, inefficiency in countries such as Croatia and Bulgaria was primarily due to internal factors initially. However, these internal factors have become less important compared to the effect of external

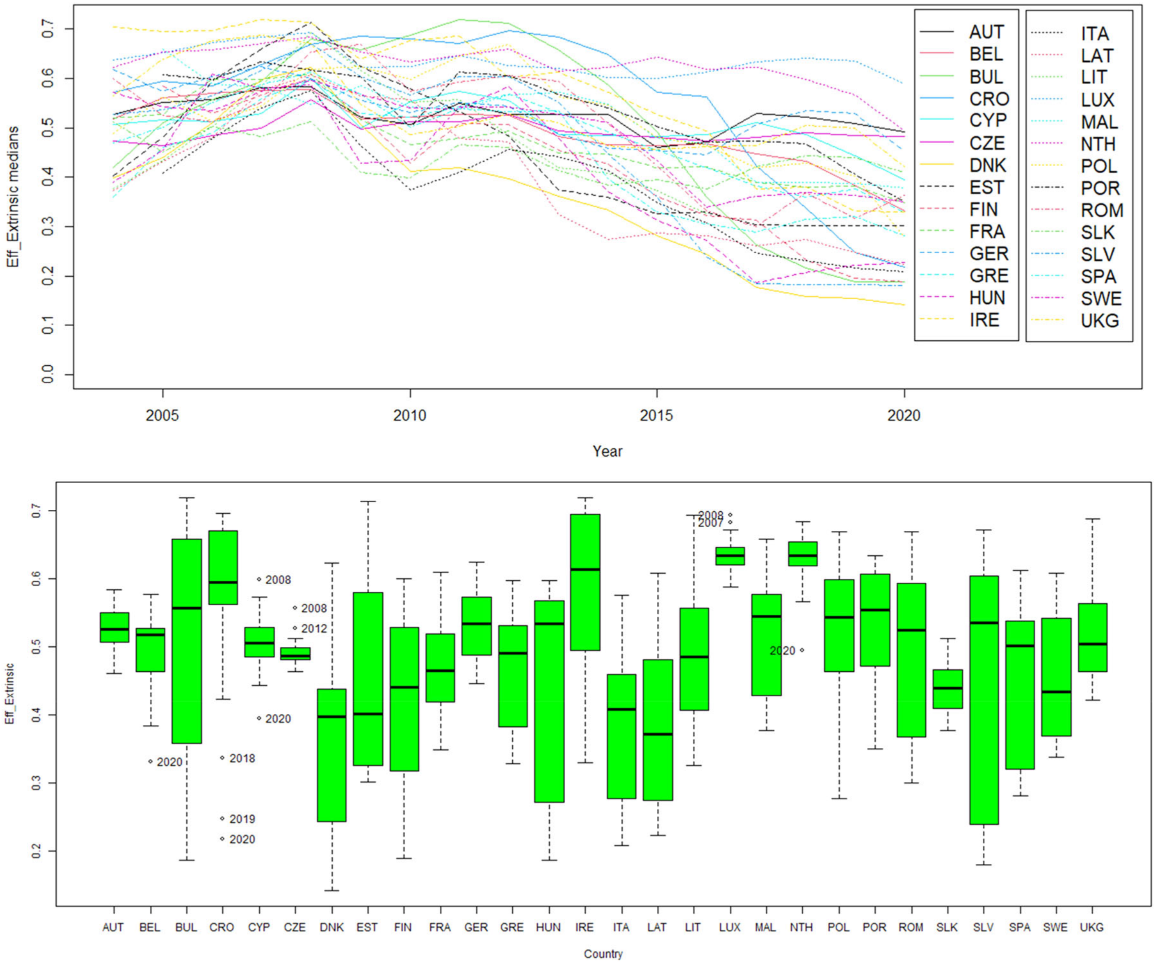


**FIGURE 3** | Evolution and distribution of extrinsic efficiency across countries estimated by model M4. Top: Estimated annual evolution of the median extrinsic efficiency for each country, over time. Bottom: Boxplots summarizing the distribution of median extrinsic efficiencies for each country. [Color figure can be viewed at wileyonlinelibrary.com]

conditions. By contrast, in countries such as Austria and Cyprus, the opposite behaviour is observed.

### 4.3 | Marginal Effects

In this section, we estimate and analyse the marginal effects of intrinsic and extrinsic efficiencies as well as the effects of intrinsic (risk and size) and environmental bank characteristics, on their Cost. Using Equation (1) the marginal effects of the intrinsic and extrinsic efficiencies are given by the following expressions:

$$\frac{\partial C_{i,t}}{\partial \mathrm{TE}_{\mathrm{int}}} = -\frac{1}{\mathrm{TE}_{\mathrm{int},i,t}} \text{ for } t \in T_i; \quad i = 1, \ldots, N, \tag{6}$$

$$\frac{\partial C_{i,t}}{\partial \mathrm{TE}_{\mathrm{ext}}} = -\frac{1}{\mathrm{TE}_{\mathrm{ext},c(i),t}} \text{ for } t \in t_{\min,c(i)}, \ldots, t_{\max,c(i)}; \quad i = 1, \ldots, N. \tag{7}$$

Using Equations (1) and (2) the marginal effects of the intrinsic characteristics of a bank is given by

$$\frac{\partial C_{i,t}}{\partial z_k} = -\delta_{\mathrm{int},k}(1 - \mathrm{TE}_{\mathrm{int},i,t}) \text{ for } t \in T_i; \quad i = 1, \ldots, N \text{ and } k = 1, \ldots, 5, \tag{8}$$

while using Equations (1) and (3) the marginal effects of the environmental characteristics of a bank is given by

$$\frac{\partial C_{i,t}}{\partial w_\ell} = -\delta_{\mathrm{ext},\ell}(1 - \mathrm{TE}_{\mathrm{ext},c(i),t}) \text{ for } t \in t_{\min,c(i)}, \ldots, t_{\max,c(i)}; \quad i = 1, \ldots, N \text{ and } \ell = 1, \ldots, 7. \tag{9}$$

Note that these effects are semi-elasticities of the total cost with respect to the intrinsic and extrinsic efficiencies, as well as the risks, size and environmental characteristics of a bank. However, if these variables are expressed in logarithms, then an elasticity is measured instead. These effects quantify how sensitive Total Cost is to changes in intrinsic or extrinsic efficiencies, or to changes in each of the bank's characteristics. Given that Equations (6) and (7) are negative, an increase in these efficiencies would tend to decrease the total cost, albeit with a lower impact, as the margin for improvement is reduced given that the Total Cost of the bank is approaching its lower limit. Regarding the characteristics, the sign of the impact is

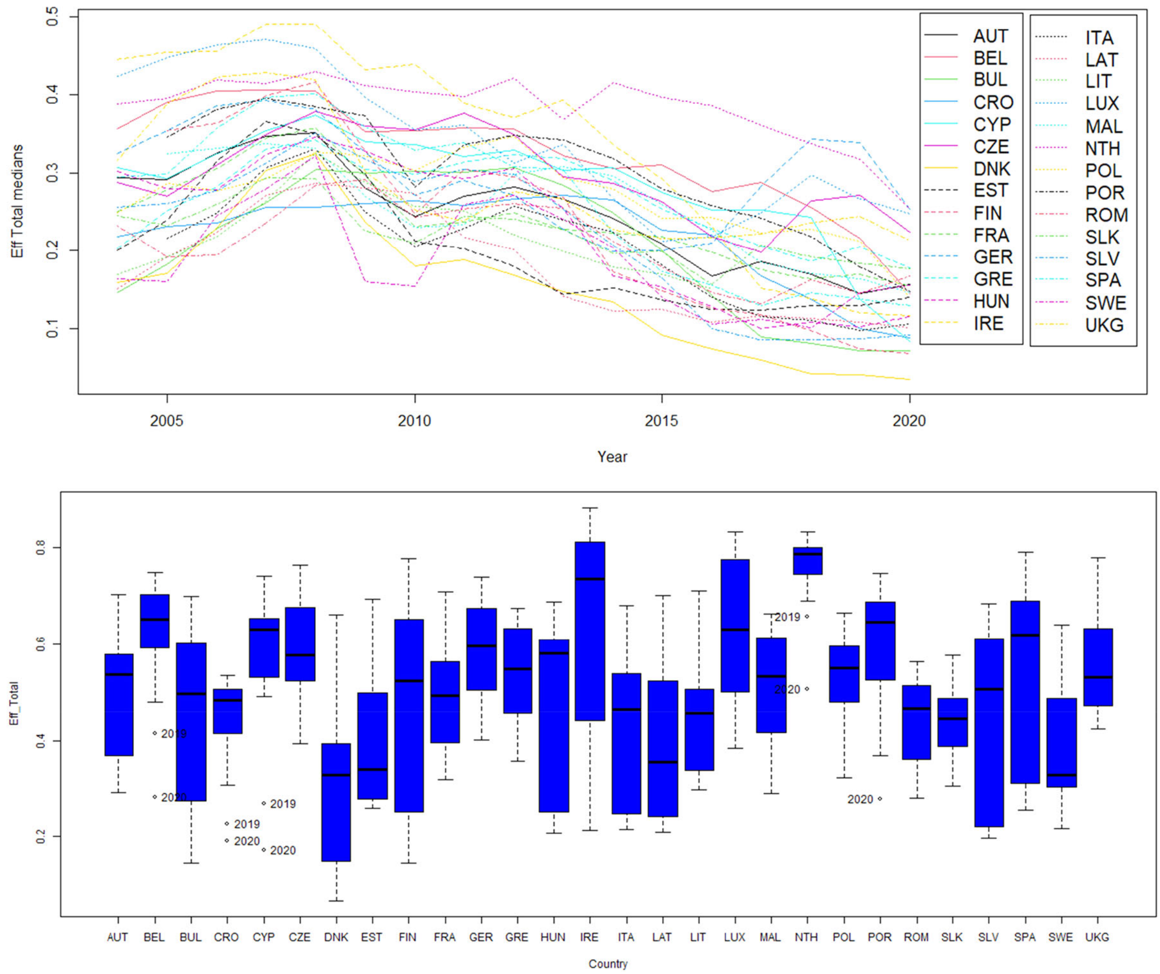


**FIGURE 4** | Evolution and distribution of total efficiency across countries estimated by model M4. Top: Estimated annual evolution of the median total efficiency for each country, over time. Bottom: Boxplots summarizing the distribution of median total efficiencies for each country. [Color figure can be viewed at wileyonlinelibrary.com]

determined by the $\delta_{\text{int}}$ and $\delta_{\text{ext}}$ coefficients, and the impact tends to be 0 if the corresponding efficiency is close to 1, as the margin for improvement with respect to the frontier tends to disappear.

Using the sample of the posterior distribution of the $\text{TE}_{\text{int}}$, $\text{TE}_{\text{ext}}$ $\delta_{\text{int}}$ and $\delta_{\text{ext}}$ parameters, we can obtain by means of the composition method applied to (6)–(9) expressions, a sample of their posterior distributions from which we can analyse the evolution of these marginal effects. Therefore, Figure 6 shows the boxplots of the bank marginal effects (6) and (8) for each year. The marginal effect for each bank is estimated by using its posterior median. The marginal effects of the intrinsic efficiencies are logically negative (greater efficiency, lower costs), with values oscillating around −1.97. The marginal effects of the risk exposures tend to be logically positive (greater efficiency, greater costs), with values oscillating around 0.57 (credit risk), 0.73 (liquidity risk), 1.17 (equity risk) and 0.06 (market risk). Finally, the marginal effects of the bank size tend to be negative, oscillating around −0.07 in such a way that the greater the bank is, the lower is its total cost because of its improvement in its intrinsic efficiency. All these effects tend to sharpen slightly (see Figure 6) but with an increasing heterogeneity along time by reflecting, indirectly, a worsening level of cost efficiency of banks (see Figure 2).

Figure 6 displays the boxplots of the marginal effects (6) and (8) for each bank and year, based on the posterior medians. As expected, the marginal effects of intrinsic efficiency are negative, indicating that higher efficiency corresponds to lower costs, with values fluctuating around −1.97. The marginal effects of risk exposures are generally positive, meaning that greater exposure is associated with higher costs: approximately 0.57 for credit risk, 0.73 for liquidity risk, 1.17 for equity risk and 0.06 for market risk. Lastly, the marginal effects of bank size are typically negative, averaging around −0.07. This suggests that larger banks tend to incur lower total costs due to gains in intrinsic efficiency. All of these effects tend to intensify slightly over time (see Figure 6), accompanied by increasing heterogeneity. This pattern indirectly reflects a gradual deterioration in banks' cost efficiency levels, as shown in Figure 2.

Figure 7 displays boxplots of the marginal effects (7) and (9) for all banks in each year. Each effect is estimated using its posterior median. As expected, the marginal effects of extrinsic efficiencies are negative, indicating that higher efficiency is associated with lower costs, with values typically centred around −1.90. These effects become more pronounced during some periods, such as 2008–2009 (−1.98) and 2015–2016 (−2.15).

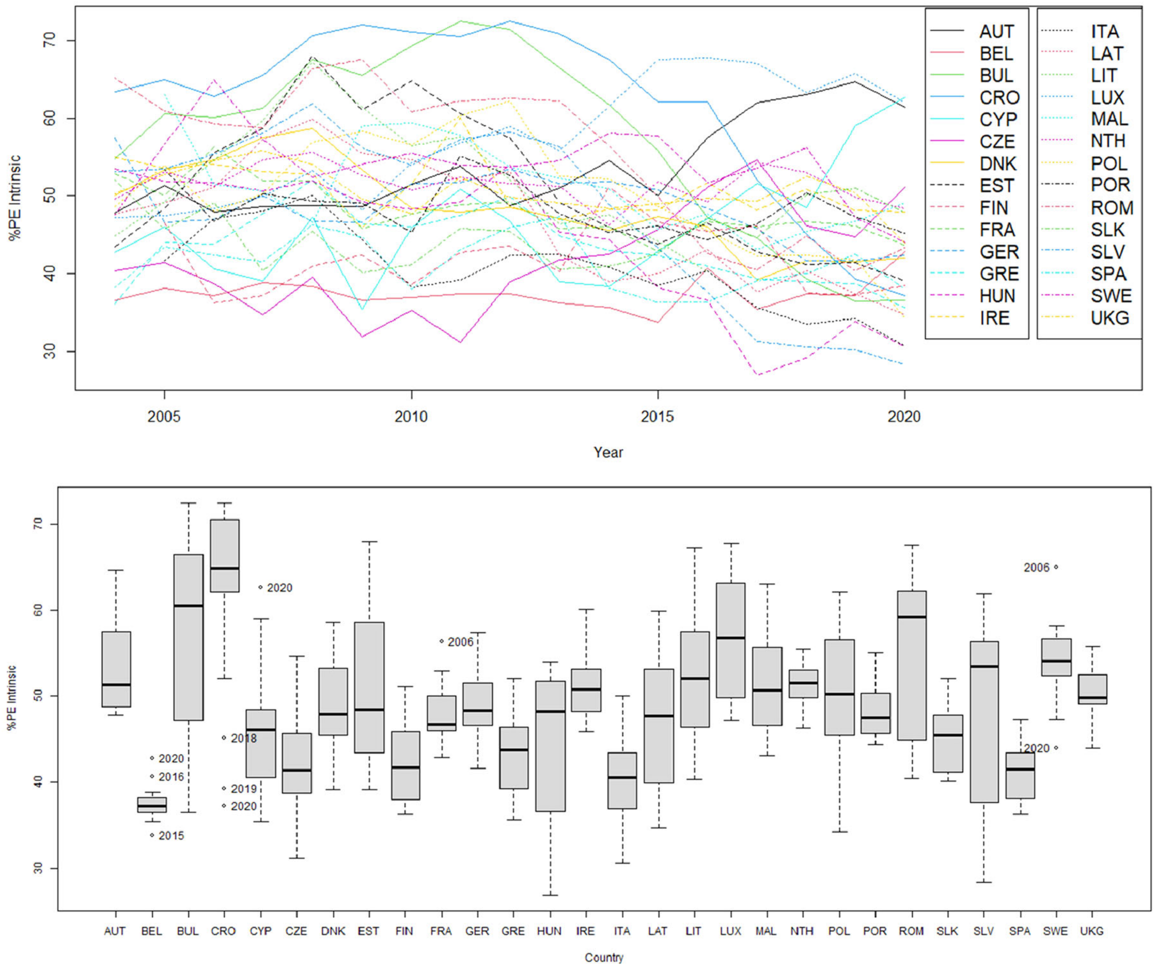


**FIGURE 5** | Evolution and distribution of the median percentage of total efficiency attributed to the intrinsic efficiency estimated by model M4. Top: Estimated annual evolution of this percentage for each country, over time. Bottom: Boxplots summarizing the distribution of this percentage for each country. [Color figure can be viewed at wileyonlinelibrary.com]

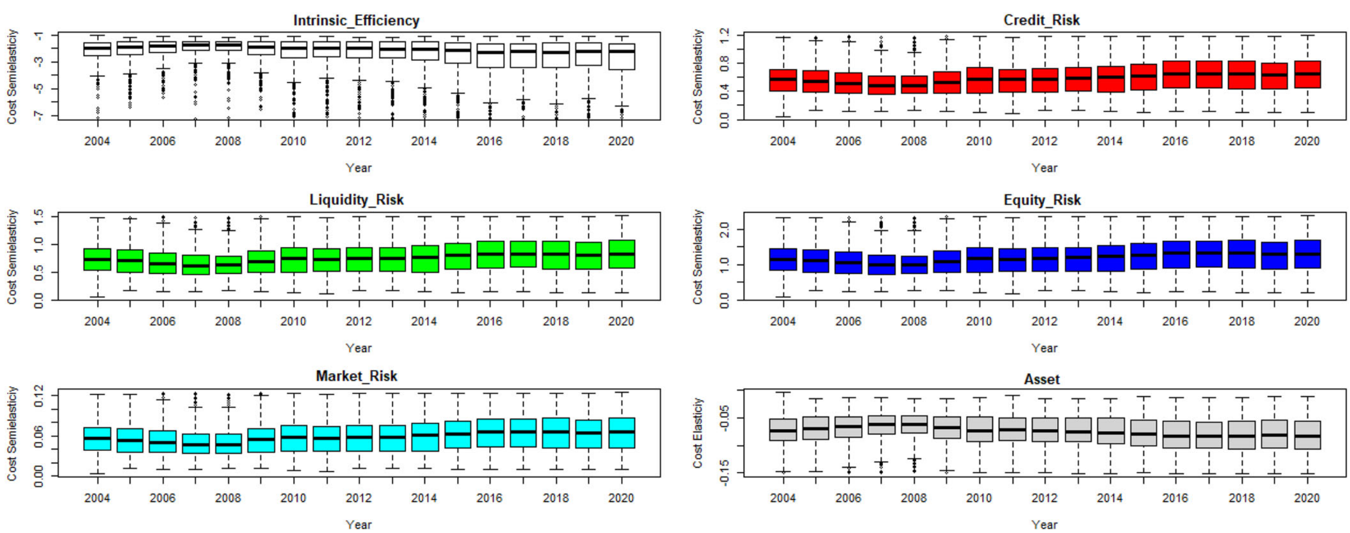


**FIGURE 6** | Annual evolution of the marginal effects of intrinsic efficiency, risk exposures and bank size on total cost estimated by model M4. This figure presents the yearly boxplots of the marginal effects estimated for each bank. The first panel corresponds to the marginal effects of intrinsic efficiency on total cost. The following panels display the marginal effects associated with each explanatory variable related to bank-specific characteristics—namely, Credit Risk, Liquidity Risk, Equity Risk, Market Risk and Asset (size). All marginal effects are computed using the posterior median for each bank and year. [Color figure can be viewed at wileyonlinelibrary.com]

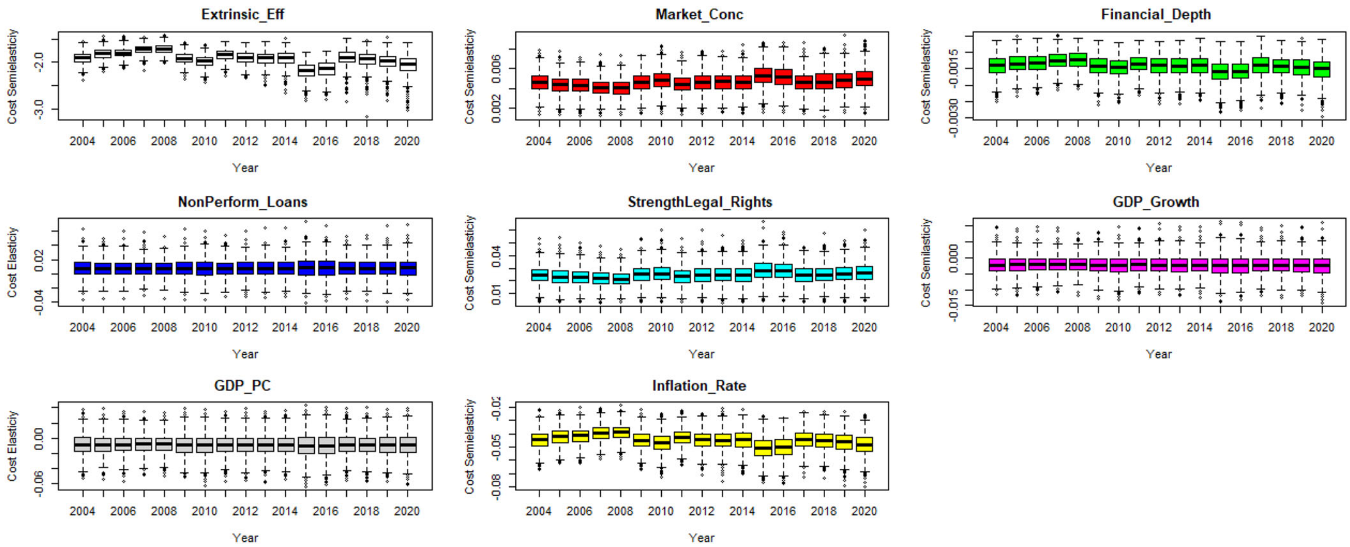


**FIGURE 7** | Annual evolution of the marginal effects of extrinsic efficiencies and environmental characteristics on total cost estimated by model M4. This figure presents the yearly boxplots of the marginal effects estimated for each country. The first panel corresponds to the marginal effects of extrinsic efficiency on total cost. The following panels display the marginal effects associated with each explanatory variable related to environment characteristics—Market Concentration, Financial Depth, Non-Performing Loans, Strength of Legal Rights, GDP Growth, GDP per Capita and Inflation Rate. All marginal effects are computed using the posterior median for each country and year. [Color figure can be viewed at wileyonlinelibrary.com]

Regarding environmental characteristics, the most notable effect is that of market concentration, which consistently has positive marginal effects (i.e., greater concentration is associated with higher cost levels), averaging at around 0.0046. Similarly, the strength of legal rights has positive effects on cost levels (approximately 0.025), suggesting that stronger creditor protections may increase compliance or operational costs. By contrast, financial depth has a negative marginal effect (approximately −0.0014), implying that deeper financial markets are associated with lower bank costs. The inflation rate also exerts a negative influence (around −0.044), indicating that inflationary environments may lead to cost-reducing adjustments.

No significant trends were observed for the remaining environmental variables. However, the marginal effects generally intensify during the 2017–2020 period, reflecting the deterioration in extrinsic efficiency levels at that time (see Figure 3).

## 4.4 | Robustness Analysis

In this section, we assess the robustness of the results presented in the previous section by examining several key aspects of the analysis. Specifically, we focus on the specification of the frontier function, the prior distributions used for the model parameters, and the composition of the data set.

### 4.4.1 | Robustness with Respect to the Frontier Function and the Prior Distribution

Regarding the frontier specification, we consider a dynamic version of the cost frontier to evaluate the impact of the economic crises that occurred during the sample period. To this end, we estimate an alternative model that incorporates time-specific effects, introducing dummy variables $I_{\text{year},t} = 1$ if $t =$ year and 0 otherwise, for year = 2005, ..., 2020:

$$c_{i,t} = \alpha_0 + \sum_{k=1}^{16} \alpha_{0,k} I_{2004+k,t} + \alpha_1 x_{i,t} + \sum_{j=1}^{4} \beta_j y_{j,i,t} + \nu_{i,t} - \log(\text{TE}_{\text{int},i,t}) - \log(\text{TE}_{\text{ext},c(i),t}), \tag{10}$$

$$\nu_{i,t} \sim N\left(0, \sigma_v^2\right); \quad t \in Ti; \quad i = 1, \ldots, N \tag{11}$$

and we assign the following prior distribution:

$$(\alpha_0 \quad \alpha_{0,1} \quad \ldots \quad \alpha_{0,16} \quad \alpha_1 \quad \beta_1 \quad \beta_2 \quad \beta_3 \quad \beta_4)' \sim N_{22}(0, 1000 I_{22}). \tag{12}$$

The remaining prior distributions are identical to those described in Equation (5).

In parallel, we considered an alternative informative prior distribution for the parameters of both models, centring the values of their parameters θ in their OLS estimators $\hat{\theta}$ obtained using the *plm* R package. The prior distribution is given by

$$(\alpha_0 \quad \alpha_1 \quad \beta_1 \quad \beta_2 \quad \beta_3 \quad \beta_4)' \sim N_6\Big((\hat{\alpha}_0 \quad \hat{\alpha}_1 \quad \hat{\beta}_1 \quad \hat{\beta}_2 \quad \hat{\beta}_3 \quad \hat{\beta}_4), \operatorname{diag}\Big(10^4\Big(s^2_{\alpha_0} \quad s^2_{\alpha_1} \quad s^2_{\beta_1} \quad s^2_{\beta_2} \quad s^2_{\beta_3} \quad s^2_{\beta_4}\Big)\Big)\Big)$$

$$\tau_v = \frac{1}{\sigma_v^2} \sim \text{Gamma}\left(1, s_v^2\right)$$

$$(\delta_{\text{int},1} \quad \ldots \quad \delta_{\text{int},5})' \sim N_5\Big((\hat{\delta}_{\text{int},1} \quad \ldots \quad \hat{\delta}_{\text{int},5})', 10^4 \operatorname{diag}\Big(s^2_{\text{int},1} \quad \ldots \quad s^2_{\text{int},5}\Big)\Big);$$

$$\tau_{\xi_{\text{int}},c} = \frac{1}{\sigma^2_{\xi_{\text{int}},c}} \sim \text{Gamma}\left(1, s^2_{\xi_{\text{int}},c}\right);\ c \in \{AUT, \ldots, UKG\}$$

$$\begin{aligned} &(\delta_{\text{ext},1} \quad \ldots \quad \delta_{\text{ext},7})' \sim N_7\Big((\hat{\delta}_{\text{ext},1} \quad \ldots \quad \hat{\delta}_{\text{ext},7})', \\ &10^4\text{diag}\left(s^2_{\text{ext},1} \quad \ldots \quad s^2_{ext,7}\right)\Big)\ \tau_{\xi_{\text{ext}},c} = \frac{1}{\sigma^2_{\xi_{\text{ext}},c}} \\ &\sim \text{Gamma}\left(1, s^2_{\xi_{\text{ext}},c}\right),\ c \in \{AUT, \ldots, UKG\}; \end{aligned} \tag{13}$$

and, in the case of (12)

$$\begin{aligned} &(\alpha_0 \quad \alpha_{0,1} \quad \ldots \quad \alpha_{0,16} \quad \alpha_1 \quad \beta_1 \quad \ldots \quad \beta_4)' \sim N \\ &\quad ((\hat{\alpha}_0 \quad \hat{\alpha}_{0,1} \quad \ldots \quad \hat{\alpha}_{0,16} \quad \hat{\alpha}_1 \quad \hat{\beta}_1 \quad \ldots \quad \hat{\beta}_4), \\ &1000\text{diag}\left(s^2_{\alpha_0} \quad s^2_{\alpha_{0,1}} \quad \ldots \quad s^2_{\alpha_{0,16}} \quad s^2_{\alpha_1} \quad s^2_{\beta_1} \quad \ldots \quad s^2_{\beta_4}\right)\Big), \end{aligned} \tag{14}$$

where $s_\theta$ is the standard error of the parameters θ To avoid imposing these prior values on the data dogmatically, we scale the variance–covariance matrices by a factor of 10,000 to obtain more diffuse priors that can be adjusted, if necessary, by the information provided by the data.

The results of this robustness analysis are reported in Table 7 and in Section SM4 of the Supporting Information. Although the MAD, COV and $R^2$ values for the dynamic frontier model (10) are somewhat lower, reflecting the higher number of estimated parameters, the WAIC values tend to be higher, indicating a worse out-of-sample predictive performance. As expected, models estimated using more informative priors generally exhibit better goodness-of-fit across most criteria than those estimated with non-informative priors.

When we analyse the estimates from the different models, we observe that the dynamic frontier model identifies lower cost levels during the financial crisis 2007–2008, a time when most banks exhibited higher efficiency scores. Conversely, higher cost levels were detected during the 2016–2020 period, which corresponded to a general decline in banking efficiency (see Supporting Information S1: Table S5). The estimated values of the remaining model parameters are highly consistent across all model specifications (see the Supporting Information). Notably, in the model with a constant frontier and informative priors—the one that performs best according to the WAIC criterion—the parameter $\delta_{nt,4}$ becomes significantly negative (see Supporting Information S1: Table S6). This result reinforces the evidence from the other models, confirming that market risk exposure is negatively associated with a bank's intrinsic efficiency. Therefore, we can conclude that our results are robust with respect to both the frontier and the prior distributions of the model.

#### 4.4.2 | Robustness with Respect to the Data Set

In this section, we assess the robustness of our results with respect to countries with limited data availability. Specifically, since Estonia, Lithuania and Malta have considerably fewer observations than the other countries in the sample, we re-estimated the model by excluding these three countries. This exercise replicates the analysis from the previous section, enabling us to evaluate the potential influence of countries with small samples on our main findings. Table 8 reports the results of this robustness check, with additional details provided in Section SM5 of the Supporting Information.

In terms of goodness of fit, the COV, MAD and $R^2$ metrics produce very similar results for all models. The constant

**TABLE 7** | Robustness check: comparison of model specifications by frontier dynamics and prior assumptions (best model highlighted in bold).

| | Non informative prior | | Informative prior | |
|---|---|---|---|---|
| **Criterion** | **Constant frontier** | **Dynamic frontier** | **Constant frontier** | **Dynamic frontier** |
| COV | 0.9452 | 0.9497 | 0.9523 | 0.9555 |
| MAD | 0.4920 | 0.4588 | 0.4971 | 0.4638 |
| $R^2$ | 0.9252 | 0.9327 | 0.9252 | 0.9328 |
| WAIC | 7101.12 | 7363.70 | **6952.11** | 7185.90 |

*Note:* This table presents the performance of four model specifications based on two dimensions: (1) whether the model uses non-informative or informative priors on the parameters and (2) whether the cost frontier is constant (no time dummies) or dynamic (includes year dummies).

**TABLE 8** | Robustness check: impact of sample composition on model performance (in bold signalled the best model).

| | Complete data Set | | Incomplete data set (without Estonia, Lithuania and Malta) | |
|---|---|---|---|---|
| **Criterion** | **Constant frontier** | **Dynamic frontier** | **Constant frontier** | **Dynamic frontier** |
| COV | 0.9452 | 0.9497 | 0.9466 | 0.9486 |
| MAD | 0.4920 | 0.4588 | 0.4951 | 0.4609 |
| $R^2$ | 0.9252 | 0.9327 | 0.9254 | 0.9328 |
| WAIC | **7101.12** | 7363.70 | **6899.82** | 7196.70 |

*Note:* This table presents the performance of four model specifications based on two dimensions: (1) whether the model uses the complete data set versus a restricted data set that excludes Estonia, Lithuania and Malta—countries with limited observations, and (2) whether the cost frontier is constant (no time dummies) or dynamic (includes year dummies).

frontier model achieves the best WAIC performance. When comparing parameter estimates, the dynamic frontier model extends the period of elevated cost levels through 2015–2020 (see Supporting Information S1: Table S11). Once again, the constant frontier model with informative priors identifies a significantly negative effect of market risk exposure ($\delta_{\text{int},4}$) on intrinsic efficiency (see Supporting Information S1: Table S12), which reinforces the findings suggested by the other models. Overall, these results confirm that our main conclusions remain robust with respect to the composition of the data set.

Therefore, our study provides a robust framework for gaining detailed insights into the efficiency dynamics of both countries and individual banks. By decomposing efficiency into intrinsic (bank-specific) and extrinsic (environmental) components, the analysis provides a nuanced understanding of performance at multiple levels. This level of detail enables stakeholders to identify specific areas of strength or inefficiency and develop more targeted and effective strategies for improving banking performance.

In the Supporting Information, we expand upon this analysis by providing graphical illustrations of the local temporal evolution of efficiency. Specifically, Section SM2 presents the efficiency trajectories of selected countries, demonstrating the model's ability to capture national trends and helping policymakers to assess the macro-level implications. Section SM3 shifts the focus to individual institutions, providing a detailed examination of the ways in which internal and external factors influence the bank performance at the microlevel.

These complementary analyses demonstrate the flexibility and precision of our modelling approach. They support informed decision-making and lay a solid foundation for targeted policy interventions and strategic improvements.

## 5 | Conclusions

In this study, we have analysed the dynamic evolution of cost efficiency within the framework of financial institutions operating in the European context. The approach has used breaks down cost efficiency into two parts: one, named as intrinsic efficiency, related to how the bank operates internally; the other, named as extrinsic efficiency, influenced by its external environment. The intrinsic efficiency looks at the bank's own characteristics and management practices that contribute to increase their efficiency. The extrinsic efficiency considers broader factors like economic conditions, regulations and market dynamics of its country that affect how efficiently banks operate. By examining both internal and external factors, this study has aimed to provide a thorough and detailed analysis of what shapes the efficiency of financial institutions in Europe.

The impact of risk variables on banking efficiency aligns with expectations, revealing that higher exposures to credit and market risk correlate with lower efficiency, while exposures to liquidity and capitalization risks associate with higher efficiency. Furthermore, the positive influence of bank size on cost efficiency suggests that larger banks tend to exhibit higher efficiency.

Crucially, two country-related covariables, market concentration and strength of legal rights, emerge as significant negative influencers of banking efficiency. In contrast, financial depth and inflation rate exhibit a significant positive influence. The precision in the error terms indicates a smooth evolution of banking efficiencies over time and across countries.

During the period under study, we have observed a widespread decline in cost efficiency across most European countries, primarily driven by a deterioration in extrinsic efficiency, that is, efficiency associated with macroeconomic and sectoral conditions. By contrast, intrinsic efficiency—linked to internal bank characteristics such as size and risk exposure—exhibited a more stable pattern over time. However, the relative importance of intrinsic and extrinsic factors varies substantially across countries and periods. This heterogeneity highlights the need for adaptive and context-specific policies and management strategies that consider both structural environmental conditions and the unique characteristics of individual financial institutions.

Importantly, the results remain robust when subjected to a range of sensitivity analyses. Specifically, our findings remain consistent whether or not time variation is incorporated into the frontier, confirming that temporal shocks, such as financial crises, do not materially distort the main conclusions. Additionally, we verify that excluding countries with limited data availability (a step taken to guard against potential survivorship bias) does not significantly alter the results. Finally, given the Bayesian framework of the model, we have tested different prior specifications, including informative priors based on external estimators. We have confirmed that the estimates remain stable across these alternatives. This robustness reinforces the reliability of our conclusions and supports their applicability across diverse empirical contexts.

Furthermore, the model's ability to provide granular analyses at both the country and bank levels makes it a valuable tool for designing tailored policy interventions. This flexibility is particularly relevant when it comes to addressing institution-specific challenges while taking into account country-level economic realities. By identifying internal and external sources of inefficiency separately, the study enables a more accurate diagnosis of performance gaps and highlights concrete areas for improvement.

In summary, this study offers a deeper understanding of the drivers of banking efficiency in Europe and provides a solid foundation for future research and targeted interventions to enhance operational performance and promote greater efficiency in the European financial sector.

One limitation of this study is that it focuses solely on commercial banks within the EU-28 countries, neglecting factors affecting other regions and types of banks, which may introduce selection bias into the results. Future research should explore other regions with different environmental conditions, including those outside Europe, to determine whether the observed efficiency disparities persist to the same extent or if varying environmental factors lead to different outcomes.

A promising avenue for future research involves investigating whether the impact of bank-specific characteristics on cost efficiency varies across countries. While our study assumes a uniform impact of risk on efficiency across banks and countries (also common in the literature), this hypothesis could be non-realistic. Future research could scrutinize whether this influence is consistent globally, implementing a hierarchical modelling approach in two stages can unveil variations in the impact of risk, considering both country-specific and bank-specific factors. This approach would offer a more nuanced understanding of how risk dynamics intersect with diverse contextual settings.

Complementing our analysis on cost efficiency, future research could extend the investigation to profit efficiency. A parallel study exploring the factors influencing banks' profitability, using a similar framework, would provide a comprehensive perspective on the operational dynamics of financial institutions. This dual analysis can offer insights into the holistic efficiency landscape.

Integrating socioeconomic and environmental dimensions into the efficiency model represents an additional research line for future exploration. Assessing how banks' balance financial performance with social and environmental responsibilities can contribute to the evolving field of sustainable banking practices. A comprehensive understanding of banks' responsiveness to broader societal and environmental concerns is essential for shaping responsible financial strategies.

Building on our aggregate-level findings, future research could conduct a detailed micro-level analysis using hierarchical modelling. This approach would allow for a more granular examination of specific banks, unravelling the intricate interplay between their unique characteristics, risk profiles and the environments in which they operate.

Investigating the nuanced impact of regulatory frameworks on banking efficiency remains an important area for further exploration. Assessing how different regulatory approaches influence cost structures, risk management practices and overall efficiency can guide policymakers in designing targeted and effective regulatory strategies.

By pursuing these research directions, scholars can contribute to a more nuanced understanding of the factors shaping banking efficiency, providing actionable insights for both academic discourse and practical applications in the financial industry.


### Acknowledgements

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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Endnotes

[1] Although it is common in the literature to treat labour cost separately, data on personnel expenses were either missing or unavailable for some sample banks. Therefore, following the works mentioned above, we used a broad measure for the price of these inputs.

[2] A translog specification and a Cobb–Douglas model with time effects were also tested in an attempt to capture the evolution of technology. However, in both cases, the estimation algorithm failed to converge, likely due to the high number of model parameters and the presence of some banks with a limited number of observations (4 or 5).

[3] We assume that the error terms of (3) and (4) are uncorrelated. Notice that this not imply, necessarily, that both efficiencies are independent because variables $Z$ and $W$ can be correlated.

[4] Notice that the term $\alpha_0 - \log(\mathrm{TE}_{\mathrm{int},}) - \log(\mathrm{TE}_{\mathrm{ext}})$does not change if $\mathrm{TE}_{\mathrm{int}}$ is multiplied by a constant $K_{\mathrm{int}} > 0$, $\mathrm{TE}_{\mathrm{ext}}$ is multiplied by a constant $K_{\mathrm{ext}} > 0$ and $\alpha_0$ is changed to $\alpha_0 \log(K_{\mathrm{int}})+\log(K_{\mathrm{ext}})$. We choose $K_{\mathrm{int}}$, $K_{\mathrm{ext}}$ such that $\mathrm{Med}(s_{\mathrm{int}}|\mathbf{Z}=\mathbf{0}) = \mathrm{Med}(s_{\mathrm{ext}}|\mathbf{W}=\mathbf{0}) = 0$ and let $\alpha_0$ vary freely.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Supplementary Material.