Center for Economic Institutions

Working Paper Series

No. 2021-2

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June, 2021

Center for Economic Institutions

Working Paper Series

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CEI Working Paper Series No. 2021-2
June 2021

Bank Survival Around the World
A Meta-Analytic Review *

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Abstract: Bank survival is essential to economic growth and development because banks mediate the financing of the economy. A bank's overall condition is often assessed by a supervisory rating system called CAMELS, an acronym for the components Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk. Estimates of the impact of CAMELS components on bank survival vary widely. We perform a meta-synthesis and meta-regression analysis (MRA) using 2120 estimates collected from 50 studies. In the MRA, we account for uncertainty in moderator selection by employing Bayesian model averaging. The results of the synthesis indicate an economically negligible impact of CAMELS variables on bank survival; in addition, the effect of bank-specific, (macro)economic, and market factors is virtually absent. The results of the heterogeneity analysis and publication bias analysis are consistent in terms that they do not find an economically significant impact of the CAMELS variables. Moreover, best practice estimates show a small economic impact of CAMELS components and no impact of other factors. The study concludes that caution should be exercised when using CAMELS rating to predict bank survival or failure.

Keywords: bank survival, bank failure, CAMELS, meta-analysis, publication selection bias
JEL Classifications: C12, D22, G21, G33

* We are grateful for numerous insightful suggestions from Tomáš Havránek and Tom Stanley. We also benefited from helpful comments by Jerome Geyer-Klingeberg, Bob Reed, Petr Teplý, and two anonymous referees. We thank Michie Kano, Hedvika Marie Kočendová, and Eriko Yoshida for their research assistance, and Tammy Bicket and Rick Stock for their editorial assistance. Kočenda acknowledges hospitality of the Kyoto Institute of Economic Research. We also acknowledge the financial support of GAČR Grant No. 20-17044 (Kočenda), as well as that of the Japan Center for Economic Research and the Zengin Foundation for Studies on Economics and Finance (Iwasaki). The usual disclaimer applies.

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1 Introduction and Motivation

Bank survival is essential to economic growth and development because banks mediate the financing of the economy. A bank's overall condition is often assessed by a supervisory rating system called CAMELS, which is an acronym for the variables Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk (details on each of these components are provided in Section 2). Since the early 1990s, various indicators of CAMELS variables have been used to explain and study bank survival (Whalen, 1991; Barr et al., 1994; Cole and Gunther, 1994). However, the CAMELS system failed to provide a warning of numerous bank failures during the global financial crisis (GFC) of 2007–2008, raising questions about the effectiveness of CAMELS in predicting bank viability. How strongly are the CAMELS indicators related to bank survival? Are the effects reported in scholarly journals the result of publication selection bias (Ioannidis et al., 2017; Andrews and Kasy, 2019)?

To tackle these under-explored research questions, we conduct a comprehensive meta-analysis of the rich empirical literature on bank survival. To the best of our knowledge and confirmed by a recent review of meta-analysis in finance (Geyer-Klingeberg et al., 2020), this is the first meta-analytic assessment of bank failure determinants.[1]

The CAMELS supervisory rating system was originally developed in 1979 in the U.S. to provide a convenient summary of bank conditions at the time of an exam; it was amended in 1997 to account for sensitivity to market risk (Lopez, 1999). The rating is used by key federal banking supervisors (the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC)) and other financial supervisory agencies in the U.S. The system was also gradually implemented outside the U.S. by various banking regulatory supervisors. CAMELS consists of six components. Ratings are assigned for each component as well as the bank's overall financial condition. Ratings are assigned on a scale from 1 to 5. Banks with ratings of 1 or 2 are considered to present few, if any, supervisory concerns, while banks with ratings of 3, 4, or 5 represent moderate to extreme degrees of supervisory concern (Lopez, 1999). The ratings are assigned based on an analysis of the bank's financial statements, together with on-site examinations.

[1] In a recent survey of meta-analysis applications in finance research, Geyer-Klingeberg et al. (2020) identified surprisingly few systematic reviews of banking. There are only six such meta-analyses and they concern banking efficiency (Iršová and Havránek, 2010; Aiello and Bonanno, 2016 and 2018), relationship lending (Kysucky and Norden, 2016), and bank competition and financial stability (Žigraiová and Havránek, 2016; Bandaranayake et al. 2020 [the last study is not included in Geyer-Klingeberg et al. (2020)]). However, none of these meta-analyses investigate bank survival/failure or the impact of CAMELS.

The rating system was developed as a practical tool to be used by banking supervisory bodies and it provides essential information on the overall condition of a bank in numerical form (Peek et al., 1999). However, the ratings are provided only to the top management of the banks and are not publicly released.[2] The private character of the CAMELS ratings means that researchers and analysts are unable to use them when studying bank conditions. However, studies can be produced using various bank-level data as proxies for the six CAMELS rating components (Jin et al., 2011). The rating system was not intended as a source of input data for academic studies, but a rich empirical literature using the proxies and analyzing the impact of CAMELS on bank survival/failure has evolved over time (details on this literature are provided in Section 2). We systematically explore the existing literature to find patterns. From this literature we collect more than two thousand estimates for this study. Despite the impressive amount, the empirical impact of CAMELS variables varies widely both in terms of direction and extent.

One might speculate that better ratings would correlate with a better chance for survival and a lower likelihood of failure. However, CAMELS classifies a bank's present condition, so it is not necessarily a good predictor of the future of a bank. To find out if CAMELS is a good predictor, we need to see how relevant CAMELS is as a determinant of bank survival. If CAMELS ratings are used by financial authorities globally to track problematic banks, we need to know what kinds of variable are important in the literature, both in statistical and economic senses. The patterns that we trace in our analysis provide some policy-relevant answers.

Banks do not operate in isolation; they are linked to the surrounding environment. The extant literature shows that a number of bank-specific characteristics and variables that characterize economic and market development are used together with CAMELS in survival/failure analyses (Demirgüç-Kunt and Detragiache, 1998; Boyd and De Nicolo, 2005; Arena, 2008; Männasoo and Mayes, 2009). Since economic, market, and institutional development vary substantially around the world, it is a reasonable prior that banks operating in more favorable economic and market conditions face a better probability of survival than their counterparts in worse environments. Such differences might play an even more important role during extreme periods such as the global financial crisis (Berger and Bouwman, 2013; Lin and Yang, 2016). For that, we explore heterogeneity in economic and market conditions by investigating the role of variables other than CAMELS and include nine

[2] The intention is to prevent a run on a bank that receives a low CAMELS rating. Banks with deteriorating conditions and declining CAMELS ratings are subject to increased supervisory scrutiny. Failed institutions are eventually subjected to a formal resolution process designed to protect retail customers.

bank-specific characteristics and (macro)economic indicators (firm size, listed on a stock exchange, firm age, foreign ownership, market concentration, GDP growth, inflation, interest rate, and stock market volatility).

Finally, a potential source of differences in the reported results can stem from differences in empirical approaches such as the definition and measurement of the probability of survival/failure, the employed data type (cross-section versus panel data), and the estimation procedures. Key modelling approaches used in the primary studies are logit/probit models and hazards models. Both types of model quantify the link between CAMELS and bank survival/failure somewhat differently and also employ specific data types. Therefore, we analyze the links between different types of models where the regression coefficients are comparable by having the same independent and dependent variables.

In our meta-analysis, we explicitly deal with publication selection bias and various sources of heterogeneity existing in the primary studies (Stanley and Doucouliagos, 2012). We also employ Bayesian model averaging (BMA) to identify the key moderators important to explain the heterogeneity of results. We perform a meta-synthesis and meta-regression analysis (MRA) using a total of 2120 estimates extracted from 50 primary studies. Results derived from the extant literature on bank survival resonate with the argument that sound corporate and financial management should help banks survive. However, the results of our meta-analysis show that there is no economic impact. We also perform a best practice estimation and show that the impact of the CAMELS variables is not absent. However, even the best practice estimates exhibit only low economic significance. There is no impact of controls (bank-specific and macroeconomic factors), though. Our meta-analysis consistently and robustly shows that the role of CAMELS as determinants of bank survival is limited at best. However, we admit that there might be no genuine effect of CAMELS on bank survival or that the applied methods (including the measurement of the effect through partial correlations) do not allow detecting an effect. Moreover, the CAMELS factors themselves, which are measured in the primary studies by observable proxy variables, might impact the results as well. These issues are mostly beyond our control, though.

The rest of the paper is structured as follows. We review CAMELS in the bank survival literature in Section 2. In Section 3, we provide details regarding the selection of the literature that constitutes the source of our data pool. The meta-synthesis is presented in Section 4. Publication selection bias is covered in Section 5. The meta-regression analysis and its results are presented in Section 6, followed by a discussion in Section 7 that also includes the best practice estimation. Section 8 provides conclusions.

2 CAMELS in the Literature

As we stated earlier, because of the strictly private character of the CAMELS rating, researchers and analysts exploit various bank-level data to obtain proxies for the six CAMELS components when studying bank conditions (Jin et al., 2011). Recent empirical literature on the failure or survival of individual banks rests heavily on the use of such CAMELS proxies (Cole and White, 2012; Pappas et al., 2017; Aliyu and Yusof, 2017; Carmona et al., 2019). There are typical proxies employed for each of the CAMELS components. The capital adequacy ratio or various ratios that involve a bank's net income are often employed to quantify its Capital adequacy (C). Asset quality (A) is usually proxied by the non-performing loan ratio, loan-loss provisions, or other measures involving the extent, type, and quality of loans. Measures such as the loan-to-deposit ratio or the total asset growth rate are used to quantify the elusive concept of Management quality (M). Earnings (E) are typically proxied by net profit margin, return on assets (ROA), or return on equity (ROE). The leverage ratio, the liquidity reserve ratio, or the ratio of current assets to total assets is a convenient proxy for Liquidity (L). Finally, Sensitivity to market risk (S) can be proxied by a ratio of the difference in the long-run and short-run interest rates to earning assets or various measures sensitive to interest rates. Many proxies exist for each CAMELS component; the above examples serve only as typical specimens. Other bank-specific characteristics and (macro)economic variables are also widely used as controls in survival and failure analyses. The substantial freedom with which both sets of variables are used in the empirical literature suggests a potentially wide array of interpretations.

The literature linking the characteristics of individual banks, represented by CAMELS proxies, with the probability of failing or surviving is heavily skewed toward banks from developed markets, especially the U.S. This is understandable, since the literature itself emerged from analyzing the U.S. banking sector. In an early paper, Lane et al. (1986) employed standard financial ratios to analyze survival predictions using a moderate sample of U.S. banks and showed the predictive power of the ratios. Whalen (1991) and Wheelock and Wilson (2000) followed a similar strategy and showed similar results based on a wider sample. Further additions mapping the survival of U.S. banks include, for example, Cole and Gunther (1995), Hwang et al. (1997), Calomiris and Mason (2003), DeYoung (2003), Cebula (2010), Cole and White (2012), Berger and Bouwman (2013), Abou-El-Sood (2016), and Carmona et al. (2019). These studies employ different sets of standard financial indicators to proxy for CAMELS components and complement them with other bank-specific variables (bank size, age, corporate structure, etc.) and various (macro)economic controls. The literature based on U.S. banks shows that standard financial indicators of a bank's condition are important in explaining bank survival/failure and various proxies for economic development (real estate investments, unemployment, stock market volatility, etc.) often improve predictions.

The European Union (EU), or the group of developed markets in Europe, is well-researched (e.g., Westgaard and der Wijst, 2011; Betz et al., 2014; Mare, 2015; Calabrese and Giudici, 2015), as are other developed markets (e.g., Evrensel, 2008; Fiordelisi and Mare, 2013; Vazquez and Federico, 2015; Wang et al., 2019). On the other hand, emerging markets are much less covered, potentially because data are not readily available. Still, the literature assesses aspects of bank failures in various individual emerging markets. This includes, for example (in alphabetical order), Argentina (Dabós and Escudero, 2004), Brazil (Sales and Tannuri-Pianto, 2007; Alves et al., 2014), Croatia (Kraft and Galac, 2007), Colombia (Gonzales-Gomez and Kiefer, 2009), Nigeria (Babajide et al., 2015), Russia (Carree, 2003; Peresetsky et al., 2011; Fungáčová and Weill, 2013; Mäkinen and Solanko, 2018), and Venezuela (Molina, 2002). Wider coverage based on regions is provided in studies of East Asia (Bongini et al., 2001; Lin and Yang, 2016), Latin America (Gonzalez-Hermosillo et al., 1997), East Asia and Latin America (Arena, 2008), Africa (Abiola et al., 2015), Central and Eastern Europe (Peresetsky et al., 2011; Kočenda and Iwasaki, 2020), or the Middle and Far East (Pappas et al., 2017; Alandejani et al., 2017). Similar to analyses of bank survival in developed markets, the above studies show the importance of the financial performance indicators represented by CAMELS proxies. But they also employ a wide array of other bank-specific characteristics and (macro)economic variables. Heterogeneity in the coverage of countries and the under-representation of emerging markets create further potential for differences in the reported impact on bank survival and failure. These differences are also grounded in, for example, various levels of banking sector development and its reform (Santarelli, 2000; Alandejani et al., 2017), different quality of relevant institutions (Fidrmuc and Süss, 2011; Kočenda and Iwasaki, 2020), or the prevailing economic conditions (Arena, 2008; Lin and Yang, 2016).

3 Literature Selection and Relevant Facts About the Data

In this section, we describe our procedure for selecting literature and review the studies selected for meta-analysis.

With the goal of finding studies that empirically examine the impact of a wide range of characteristics on a bank's ability to survive, we first searched the Web of Science database for research studies with keywords *bank* and *survival* and one of the following: *failure* or *crisis* or *analysis*. We further searched Google Scholar for studies using the keywords *bank survival* or *bank failure* and one of the following: *default*, *probability*, *distress*, or *crisis*. The literature search was carried out in February 2021. As a result of this mechanical search, we first individually examined approximately 450 studies, narrowing the list to 157 studies that had promise of being applicable to the goals of this paper. In practice, each study had to (i) provide an assessment of bank survival or default and (ii) contain estimated coefficients associated with financial indicators for CAMELS proxies, other bank-specific variables (bank size, age, corporate structure, etc.), and various (macro)economic controls, with reasonable statistical significance.

Based on the above criteria, we examined the contents of the relevant research studies one by one in detail, further narrowed our sample, and finally selected 50 studies in total. As reported in Table A1 in the Appendix, these 50 selected studies consist of 48 journal articles, 1 book chapter, and 1 unpublished manuscript (a thesis). The earliest studies date to the early 1990s (Whalen, 1991; Barr et al., 1994; Cole and Gunther, 1994), while the most recent was published 2021 (Markoulis et al., 2021). Most of the studies in the sample were published after 2010. The 50 selected studies provide estimates based on data that cover a wide range of years (Table A1). An exceptional time span is covered in Liu and Ngo (2014): the period from 1934 to 2012. Otherwise, studies cover the 1980s (1984–1989) to 2017 (Mäkinen and Solanko, 2018; Petropoulos et al., 2020) and all the years in between. The average period covered by the studies is 10.7 years and the median is 7 years.

From the 50 selected studies, we collected a total of 2120 estimates of the CAMELS variables; details are presented in Tables 1 and A1. In addition, we gathered 777 estimates unevenly divided among nine bank-specific characteristics and (macro)economic indicators (firm size, listed on a stock exchange, firm age, foreign ownership, market concentration, GDP growth, inflation, interest rate, and stock market volatility). The mean and median of the collected estimates per study are 57.9 and 35.5, respectively.

We are able to distinguish economically different periods before, during, and after the financial crisis. Based on these divisions, we can divide the data estimates into those that reflect the pre-GFC (791 estimates), GFC (1040 estimates), and post-GFC (289 estimates) periods (see Table 1). The post-GFC period has the lowest number of estimates, with a short time span from then to now. The destructive GFC period attracts understandable attention and provides the majority of estimates. We are also able to distinguish country/region coverage. Receiving the most attention is the U.S. or North America, followed by Europe and the emerging markets (Table A1). Finally, the overwhelming majority of the studies we analyze were published in academic journals (Table A1).[3]

[3] The literature search was carried out by a research assistant and both authors. The selection of articles for close examination was carried out by both authors. The coding of studies was carried out and cross-checked by both authors. A few disagreements in coding were solved via second round of inspection of primary studies and clarification to eliminate remaining uncertainty. Hence, the literature

There are two types of data transformation we needed to perform before running the meta-analysis. First, a number of the studies employ various hazards models to assess survival/failure probability. In the case of the non-parametric Cox proportional hazards model, no transformation is needed. If a variable estimate is greater than 1, we may consider the variable to be a risk factor that decreases the probability of bank survival and increases the probability of bank failure. Similarly, if an estimate is below 1, such a determinant is considered to reduce the probability of failure and increase the probability of survival. However, the situation might be different for the "parametric hazards" or "other hazards models" in our database. We carefully checked the original papers employing these two categories of hazards models and transformed the data in just five instances where we found inconsistencies between the estimates' signs and those of the Cox hazards model. The transformation involved simply reversing the sign of the effect (estimate) to be consistent across the models. Transformed estimates were then used with the rest as input data for the meta-analysis. Second, individual variables that are proxies for specific CAMELS variables are identified in the literature with their predicted signs with respect to survival or failure. For example, the ratio of total loans to total assets is conventionally associated with an increased survival probability (positive predicted sign), while the ratio of non-performing loans/total assets is conventionally associated with a decreased survival probability (negative predicted sign). Both variables are often employed as proxies for the same category of Asset (quality), though. Therefore, in similar cases, we have reversed the signs of estimates of some CAMELS variables for the purpose of meta-analysis in order to be able to synthesize estimates whose predicted signs seem to be inconsistent with each other.

In the next sections we proceed with a quantitative assessment of the collected estimates: meta-synthesis, assessment of publication selection bias, and meta-regression analysis (MRA). In our approach, we follow contemporary methods for meta-analysis outlined by Geyer-Klingeberg et al. (2020) and strive to comply with the reporting guidelines for meta-analysis in economics as recently summarized by Havránek et al. (2020).

4 Meta-Synthesis

We perform the meta-synthesis of the collected estimates by employing a partial correlation coefficient (PCC) that measures the association of a dependent variable (survival probability) and the independent variable of interest (a CAMELS variable) when other variables are held

search as well as the process of coding the selected studies conforms to the recent guidelines published in Havránek et al. (2020). The data that support the findings of this study are available from the corresponding author upon reasonable request.

constant. We use a PCC-based assessment because PCC is a unitless measure suitable for the aggregation of multiple studies that use an array of different models to assess bank survival/failure probability when the units and/or definitions of variables vary among the selected papers (Stanley and Doucouliagos, 2012). PCC is defined as:

$$PCC_k = \frac{t_k}{\sqrt{t_k^2 + df_k}}, \tag{1}$$

where t_k and df_k denote the t value and the degree of freedom of the k-th estimate, respectively; $k = 1, 2, \ldots, K$. The number of degrees of freedom (df_k) is available from all the studies and it is the number of observations minus the number of estimated coefficients. The standard error (SE) of PCC_k is given by $SE = \sqrt{(1 - PCC_k^2)/df_k}$.

Values of PCC can range from –1 to 1. Irrespective of whether the association between variables is positive or negative, Cohen (1988) defines a coefficient of 0.5 as the threshold between medium and large effects and a coefficient of 0.3 as the threshold between small and medium effects. A correlation of 0.1 is the lowest threshold of an economically meaningful effect; if the correlation is less than 0.1, it means that the effect is negligible. By using PCC to quantify the association between CAMELS variables and the probability of survival/failure, we emphasize aggregating these associations in terms of direction and statistical significance. By using a unit-less measure we are also able to assess the economic effect. This would be hard to capture otherwise, since the dependent variable is a survival/failure probability and not an economically or financially measured outcome. [4]

In Figure 1, we show the individual kernel densities of the PCCs for the survival/failure probability and the CAMELS variables. The aggregate distribution of the PCCs for all CAMELS shows that PCC values range within a (-0.8; +0.8) interval with a mean slightly above zero (Figure 1, panel a). We further divide the PCC estimates according to different CAMELS variables since each CAMELS variable refers to a different aspect of the condition of a bank. By dividing the PCCs in the above manner, we hope to assess the contribution of individual CAMELS variables with respect to a bank's survival/failure. The distributions of CAMELS variables do not differ significantly by type (Figure 1, panel b) or estimation period (Figure 1, panel c). Thus, a bird's-eye view of the literature suggests that

[4] The unitless property of the PCC allows for direct comparison of a wide variety of variables with different definitions and units. This property is quite beneficial for the present study. However, the unitless feature also has the disadvantage that it makes it difficult to identify elasticity of a variable, which is very crucial in some cases. Hence, the adoption of the PCC should be determined by balancing these advantages and disadvantages, taking the research aim into account.

the link between CAMELS variables and bank survival/failure probability is evenly distributed and on average very weak. It is interesting that the GFC period exhibits a highly symmetric bi-modal distribution centered at zero and the pre-GFC period exhibits a marginally larger positive effect when compared to the other two periods.[5] Potential reasons could be the differing abilities of individual banks to cope with the extreme GFC conditions and the more stable economic conditions during the pre-GFC period.

In Table 1, we report the descriptive statistics and statistical normality test results for each PCC. We report the PCCs for all CAMELS variables, as well as for several key indicators identified in the literature as potentially impacting bank survival/failure probability. This initial evidence shows that individual PCCs are skewed and exhibit substantial kurtosis. Their non-normality is also confirmed by a formal test. PCC sizes hint at a lack of economic significance. The only variables worthy of note are Sensitivity (to market risk) from the CAMELS variables and interest rate from the rest of the controls.

In order to obtain additional insights on the impact of CAMELS variables, we employ the following method to synthesize PCCs (we report the results of the meta-synthesis of the PCCs in Table 2). Suppose that there are K estimates (k = 1, 2, ..., K). With respect to the PCC of the k-th estimate (PCC_k), the corresponding population and standard deviation are labeled as θ_k and s_k, respectively. We assume that $\theta_1 = \theta_2 = \ldots = \theta_K = \theta$, implying that each study in a meta-analysis estimates the common underlying population effect and that the estimates differ only by random sampling errors. Then we define an asymptotically efficient estimator of the unknown true population parameter θ as a mean ($\bar{R}$) that is weighted by the inverse variance of each estimate:

$$\bar{R} = \sum_{k=1}^{K} w_k PCC_k / \sum_{k=1}^{K} w_k, \tag{2}$$

where $w_k = 1/v_k$ and $v_k = s_k^2$. The variance of the synthesized partial correlation mean $\bar{R}$ is given by $1/\sum_{k=1}^{K} w_k$. Specification (2) is the meta fixed-effects model. Hereafter, we denote the estimates of the meta fixed-effects model using $\overline{R_f}$ (reported in column 2 of Table 2).

Before using this method to synthesize the PCCs, we must assess whether the estimates are homogeneous; H_0: estimates of the meta fixed effects (PCC_k) are homogenous. A homogeneity test uses the statistic

[5] The observations from the graphical presentation are consistent with the meta-synthesis results presented later in Table 2.

$$Q_r = \sum_{k=1}^{K} w_k \left(PCC_k - \overline{R_f}\right)^2 \sim \chi^2(K-1), \qquad (3)$$

which has a chi-square distribution with N-1 degrees of freedom. The null hypothesis is rejected if Q_r exceeds the critical value. Based on the values reported in column 4 of Table 2, we reject the null as the estimates are heterogeneous.

Based on the above result, we assume that heterogeneity exists among the studies. We adopt a more suitable random-effects model that incorporates sampling variation for the underlying population of effect magnitudes as well as study-level sampling error. If the deviation between estimates is expressed as δ_θ^2, the unconditional variance of the k-th estimate is given by $v_k^u = \left(v_k + \delta_\theta^2\right)$. In the meta random-effects model, the population θ is estimated by replacing the weight w_k with the weight $w_k^u = 1/v_k^u$ in equation (2).[6] For the between-studies variance component, we use a method of moments estimator defined in equation (4) using the value of the homogeneity test value Q_r obtained from equation (3):

$$\hat{\delta}_\theta^2 = \frac{Q_r - (K-1)}{\sum_{k=1}^{K} w_k^u - \left(\sum_{k=1}^{K} w_k^{u^2} / \sum_{k-1}^{K} w_k^u\right)}. \qquad (4)$$

Hereafter, we denote the estimates of the meta random-effects model as $\overline{R_r}$ and report them in column 3 of Table 2.

We report the results of the traditional meta-synthesis of PCCs given above, in Table 2. Presence of heterogeneity among selected studies is clearly documented since the null of homogeneity is rejected at the 1% significance level by the Cochran Q test of homogeneity (column 4) and by the I^2 and H^2 statistics (columns 5 and 6, respectively). Hence, based on the statistical evidence, we adopt the synthesized effect size of the $\overline{R_r}$ estimates obtained from the random-effects model (Table 2, column 3) as a reference synthesis value using the traditional method, while synthesized effects from the fixed-effect model are reported only for the sake of completeness.

When we inspect the synthesized random-effects model estimates (column 3, Table 2) we see that the synthesized effects exhibit two patterns. One, some of them take up similar values as the mean PCC values reported in Table 1 (column 2) and this fact suggests that the synthesized estimates seem to be relevant indicators of the materialized effects. Two, some estimates substantially differ in size as well as direction from the mean values. The distortion might be due to publication selection bias and/or heterogeneity present in the studies.

[6] This means that the meta fixed-effects model is a special case based on the assumption that $\delta_\theta^2 = 0$.

As an alternative approach to the traditional meta-synthesis method described above, we also report the results of the unrestricted weighted least squares average (UWA) designed by Stanley and Doucouliagos (2017). The UWA approach is subject to less influence from potential publication-selection bias than random-effects model estimates. Like the synthesized effect size, the UWA takes a point estimate obtained from the regression where the standardized effect size (t_k) is the dependent variable and the estimation precision is the independent variable. Specifically, we estimate equation (5), in which there is no intercept term and the coefficient α serves as the synthesized value of the PCCs:

$$t_k = \alpha(1/SE_k) + \varepsilon_k, \tag{5}$$

where ε_k is a residual term. The estimates of α in equation (5) have the same values as the estimated value of $\overline{R_r}$, but UWA accounts for heterogeneity, while $\overline{R_r}$ does not. UWA values are reported in column 8 of Table 2 (section c). The UWA coefficient values closely resemble those of the fixed-effect model but their statistical significance is often lower (more details below).

Further, Stanley et al. (2017) proposed computing the UWA only from those estimates whose statistical power exceeded a threshold of 0.8; they called this estimation method the weighted average of the adequately powered estimates (WAAP). Stanley et al. (2017) argue that the WAAP estimate is more robust against publication selection bias and superior to other weighted averages including fixed-effects, random-effects, and the UWA itself; Ioannidis et al. (2017) further demonstrated that the WAAP is suitable for economic research. Following these arguments, whenever a WAAP estimate is available, we adopt it as the best synthesis value. If WAAP estimation failed due to a lack of adequately powered estimates, we employ the random-effects estimate as the second-best synthesis value.

In the rightmost five columns of Table 2, the results of UWA and WAAP synthesis are exhibited. In theory, the UWA models produced the same point estimate of the fixed-effect model. However, because the UWA method is more robust against publication selection bias than the fixed-effect model, the reported *t* values of the UWA tend to be much smaller than those of the fixed-effect model, as Stanley and Doucouliagos (2017) argue. With regard to the WAAP approach, it could generate a synthesized effect size for 8 variables (Asset, Sensitivity, pre-GFC period, Firm size, Listed on stock exchange, Firm age, Foreign ownership, GDP growth). Thus we adopt the WAAP estimates as the selected synthesis values for these eight variables, while the random-effects estimates are used as the selected synthesis values for the remaining 11 variables.

Figure 2 illustrates the above-selected synthesis values in a graphical comparison. The synthesis results indicate that there exist links between many CAMELS variables and bank survival probability, but these effects are economically insignificant in every respect.

Most of the other factors show some impact as well but again without economic significance. However, the above results might be affected by the existence of heterogeneity and publication selection bias. We analyze those issues in detail in the next steps, beginning with publication selection bias.

5 Publication Selection Bias

Publication bias is present in research output and Ioannidis at al. (2017) demonstrate that in economics alone the magnitude of estimates can be increased twofold because of this phenomenon. This type of bias might occur because papers that report estimates with the expected signs or conclusions are more likely to be accepted and published; as such, an examination of publication selection bias is important for meta-analysis (Stanley and Doucouliagos, 2012).

As a first step, we address this issue by forming funnel plots of the reported PCCs (Egger et al., 1997; Stanley and Doucouliagos, 2010). The funnel plot is a scatter plot with the effect size (measured by PCC in our case) on the horizontal axis and the precision of the estimate (measured by $1/SE$) on the vertical axis. In the absence of publication selection bias, the effect sizes reported by independent studies vary randomly and symmetrically around the true effect. Moreover, according to statistical theory, the dispersion of effect sizes is negatively correlated with the precision of the estimate. Hence, the shape of the plot is symmetric and resembles an inverted funnel. In other words, if the funnel plot is not symmetric but skewed in a specific direction, then one should suspect a publication selection bias. It would hint that estimates in favor of a specific conclusion (i.e., estimates with the expected sign) are more frequently published.

In Figure 3, we picture the funnel plot of the estimates for all CAMELS variables. The plot of PCCs exhibits the funnel shape with a symmetric distribution. This evidence suggests that publication selection bias (favoring results with the expected sign) is not likely to occur in empirical research that assesses the impact of CAMELS on the probability of bank survival in the selected studies listed in Table A1.

As the funnel plot is only a first-order type of assessment, we also report estimates of meta-regression models, which have been developed to examine in a more rigorous manner publication selection bias and the presence of the true effect. First, we examine publication selection bias based on the fact that in the presence of publication selection, the reported estimates are correlated with the standard errors (Stanley, 2005). Thus, following Stanley and Doucouliagos (2012), we estimate a simple regression:

$$PCC_k = \beta_1 + \beta_0 SE_k + v_k, \tag{6}$$

where SE_k is a standard error of the k-th estimate and υ_k is the error term. A nonlinear version of the equation above can be specified as:

$$PCC_k = \gamma_1 + \gamma_0 SE_k^2 + z_k, \quad (7)$$

where z_k is the error term. Both regressions are estimated as weighted least squares (WLS) with $(1/SE_k^2)$ as weights, which is equivalent to dividing the equations by SE_k (Stanley and Doucouliagos, 2017). Coefficient β_0 represents the strength of publication bias and if it differs statistically from zero, there is evidence of asymmetry in the funnel graph. In panel a of Table 3, the funnel-asymmetry test (FAT; H_0: $\beta_0 = 0$) shows that statistically worse estimates characterized by large standard errors are linked to larger PCCs. As such, the analyzed literature contains a risk of publication selection bias. However, even if there is publication selection bias, a genuine effect may still exist in the available empirical evidence. The mean underlying effect beyond publication bias is captured by intercept β_1. Stanley and Doucouliagos (2012) propose to assess its existence by testing the null hypothesis H_0: $\beta_1 = 0$. In Table 3 (panel a), the precision-effect test (PET) shows a statistically significant non-zero effect that is economically insignificant.

A nonlinear version of the FAT-PET equation above is less biased than (6) if a genuine empirical effect exists. Assessment of H_0: $\gamma_1 = 0$ constitutes the precision-effect estimate with a standard error (PEESE) test (Stanley and Doucouliagos, 2012). In Table 3 (panel b), we show that the intercept (γ_1) from the PEESE equation is even smaller (in absolute terms) than that from the FAT-PET equation, but the difference does not really matter as both coefficients are of negligible size. Based on the above we conclude that our meta-analyzed studies contain publication selection bias and do not demonstrate the economically meaningful true effect of CAMELS variables on the probability of bank survival.

In order to complete the publication selection assessment, we also perform the FAT-PET-PEESE procedure for the individual CAMELS variables for the different periods and for the individual meta-independent variables listed in Table 1. We summarize the results in Table A2 in the Appendix, where we show that the funnel-asymmetry test (FAT) rejects the null hypothesis of no bias in eight of 18 cases (Capital, Asset, Management, Sensitivity, pre-GFC, firm age, interest rate, and stock market volatility). When individual categories are inspected, the evidence shows that the likelihood of publication selection bias is quite low for meta-independent variables, but it is present for two thirds of the CAMELS variables and the pre-GFC period. However, despite the possibility of publication selection bias, the results of the PET test indicate the presence of genuine empirical evidence for three individual CAMELS variables (Capital, Asset, and Management) for the pre-GFC period and for the majority of meta-independent variables (firm age, listed on a stock exchange, foreign ownership, GDP growth, inflation, interest rate, and stock market volatility). Finally, the

PEESE method, which delivers effects adjusted for publication selection bias, shows that true effects exist for one CAMELS variable (Asset) for the pre-GFC period and for five meta-independent variables (firm size, listed on a stock exchange, foreign ownership, inflation, and stock market volatility).

The last set of results indicates that the existence of publication selection bias in the analyzed literature corresponds to the overall lack of a genuine effect after adjusting for publication selection bias. Therefore, we conclude that, in the case of CAMELS, we are unable to grasp the true effect of the individual measures. With a single exception, we provide evidence of the true but economically meaningless effect (a less than 1% numerical relationship) of Asset quality with respect to bank survival. The evidence is more favorable for meta-independent variables, where we are able to identify their genuine effect more often, although the impact is negligible.

6 Heterogeneity in the Results: Meta-Regression Analysis

During the synthesis of the collected estimates in Section 4, we detected a strong presence of heterogeneity among the studies, which was evidenced by formal testing. In the next step, we conduct an MRA to explore the factors behind the heterogeneity in the selected studies.

6.1 Selection of moderators via Bayesian model averaging (BMA)

A large number of potential explanatory variables has been identified in the studies we analyze. In Table A3 in the Appendix, we present a list of 39 meta-independent variables. These variables are considered by researchers to lead to systematic differences in the reported empirical evidence and they also reflect the debate within the bank survival literature. From the list of 39 independent variables, the CAMELS variables are of particular interest to us. We account for other characteristics relevant to bank survival and list a set of nine variables that characterize banks, market structure, or economic conditions and that are deemed by researchers to be relevant. Since there is a large variety of approaches to analyzing bank survival, we also include groups of variables that account for regional (country) coverage, estimation period, data type, econometric methodology (the estimator and controls for fixed effects in location, time, and industry), and other relevant nuances that might explain heterogeneity in the meta-analyzed results.

The array of factors that potentially affect heterogeneity among studies is large and their inclusion in a regression might be problematic. Most importantly, such an approach would disregard the problem of model uncertainty in the absence of a theoretical model. In our case, the CAMELS variables certainly motivate including them into the regression, but the rest of the factors are controls that widely differ depending on the study. Further, a large number of meta-independent variables may also cause multicollinearity. We account for these two econometrical issues by implementing the Bayesian model averaging (BMA) approach (Ahtiainen and Vanhatalo, 2012; Babecky and Havránek, 2014; Havránek and Sokolová, 2020). BMA represents an application of Bayesian inference to provide a coherent and systematic mechanism minimizing uncertainty in model choice. BMA performs regressions on subsets of potential combinations of variables and the likelihood of each model is given by the posterior model probability. Specific variables are included in the model based on the value of the posterior inclusion probability (PIP) calculated across models (Raftery et al., 1997; Eicher et al., 2011). Recent meta-studies perform BMA analyses to specify robust moderators in their meta-regression estimation and we follow this approach.

By using BMA, we identify meta-independent variables and present them in Table 4 where we report estimation results using the collected estimates of CAMELS variables (panel a) and all collected variables(panel b). Following Brada et al. (2021), we select as moderators those meta-independent variables whose PIP (which is analogous to statistical significance) exceeds a conservative threshold of 0.80; we include them in the MRA estimation reported later.[7]

6.2 Estimation

We employ the moderators selected by the BMA to estimate the meta-regression model specified as:

$$PCC_k = \delta_0 + \sum_{n=1}^{N} \delta_n x_{kn} + e_k \,, k = 1, 2, \cdots, K \,, \qquad (8)$$

where PCC_k is the partial correlation coefficient of the k-th estimate defined earlier in equation (1); x_{kn} represents the n-th meta-independent variable that captures relevant characteristics of the k-th PCC estimate and explains its systematic variation from other PCCs in the sampled literature; δ_n denotes the meta-regression coefficient to be estimated; N is the number of meta-independent variables; and e_k is the meta-regression disturbance term (Stanley and Jarrell, 2005). The above model enables relating various variables to heterogeneity in the results coming from our set of studies.

Coefficient estimates (δ_n) related to the factors are subject to the null hypothesis that H_0: factors related to specific studies (e.g., PCCs) are not relevant to the reported outcomes. To check the statistical significance of coefficient δ_n, we perform an MRA using various estimators that are potentially important to control for heterogeneity across studies. Stanley and Doucouliagos (2015) demonstrate that in the presence of publication selection bias, the unrestricted weighted least squares (UWLS) approach dominates random effects. This

[7] Eicher et al. (2011) argue that moderators with PIP between 0.99 and 1.00 exhibit a decisive impact, between 0.95 and 0.99 a strong impact, and between 0.75 and 0.95 a substantial impact.

approach provides satisfactory estimates and confidence intervals that are comparable to random effects when there is no publication bias. They also show that the UWLS approach is superior to fixed-effect meta-analysis in the presence of excess heterogeneity and it is identical to fixed-effect meta-analysis when there is no heterogeneity. Since we identified both publication selection bias and heterogeneity in the collected estimates (see Table 2), we adopt the UWLS approach.

Specifically, we use the cluster-robust weighted least squares (WLS) estimator with weights of the inverse of the standard error squared ($1/SE^2$) as a measure of estimate precision. Cluster-robust estimates use a study as a cluster variable to account for potential dependence among several estimates reported by a specific research study; robust standard errors are computed as well. Further, the number of reported estimates in the analyzed studies varies greatly and studies with many reported estimates might drive the results of an MRA. We account for this so-called "over-representativeness" issue and, as a robustness check, we employ the cluster-robust WLS estimator with weights of the inverse of the number of estimates reported per study times precision ($1/EST*SE^2$). Finally, following Stanley and Doucouliagos (2012), Havránek and Sokolová (2020), and Iwasaki et al. (2020), we also use the cluster-robust random-effects panel GLS estimator. The choice of the random-effects panel model specification is based on the Hausman test.

6.3 Results

The first set of MRA estimation results is shown in Table 5, where we focus on the CAMELS variables. Here, we take Capital (adequacy) as the reference variable estimate and assess whether and how the other CAMELS variables differ from this default category. From Tables 1 and 2 we know that the impact of Capital is negligible since its coefficient is less than 0.04. The outcome is straightforward: the coefficients of the CAMELS meta-independent variables are very small and statistically insignificant, meaning that there is no difference in impact. The effect of Management constitutes the single exception, but the extent of the effect is not economically meaningful. Both WLS estimators show that the impact of Management is negligibly (0.005) above that of Capital if other research conditions are held constant. The panel GLS estimator shows that the impact of Management is about 0.04 below that of Capital, which is a net zero effect.

The second set of MRA estimation results is reported in Table 6, where we focus on nine key factors selected via BMA (see Table 4); these factors are also identified in the literature as potentially impacting bank survival. In this step, we take all CAMELS variables as a point of reference and assess whether and how the effect of the nine variables differs from the default category (CAMELS variables). The key observation is that the sizes of the effects (measured by the partial correlation coefficient) of the seven moderators are statistically significant (by one or two estimators), are very small, and exhibit impacts that are below the CAMELS group effect. While the effects of the moderators are quite similar, the effect of the interest rate is an order of magnitude larger, although it is still below 0.12. None of the seven factors produces any systematic and economically meaningful effect on the reported results. Statistically insignificant variables are inflation and whether a bank is listed on a stock exchange.

From the BMA procedure, we isolated several moderators with the potential to explain the heterogeneity in the primary-study results.

Time periods. In Table 5, we take the pre-GFC period as a default category and show that no systematic difference exists with respect to the GFC period since the associated coefficients are statistically insignificant. However, negative estimates of the post-GFC period denote that the impact of CAMELS variables on bank survival after the crisis is associated with a lower survival probability than the impact in the pre-GFC and GFC periods. However, the magnitude of the effect is not even 5% and comes from only one estimator (panel GLS). Still, the difference among periods corresponds to the meta-synthesized effects (Table 2, column 3) reported earlier. Taken with some caution, the finding indicates that the post-GFC period, or more precisely the timespan of about five years after the GFC, could be difficult for bank development. This is not surprising; however, more important is the fact that such heterogeneity does not seem to be driven by specific research or estimation conditions in the meta-analyzed studies, but rather by the genuine hardship of the post-GFC period (Claessens and Van Horen, 2015). We explore this issue further and interact the three GFC-related periods with a set of moderators selected by the BMA to see whether the result comes from specific geographical regions or from some other variables. The results are reported in Table A4 in the Appendix and the very small size of the coefficients carries a warning against making broad conclusions.[8] In terms of regions, the probability of survival during GFC increases for banks from the Asia-Pacific region but it declines before as well as after the GFC; no other region exhibits a similar pattern due to statistically insignificant coefficients. When compared to Latin America, Eastern Europe, and the former Soviet Union, banking systems in the Asia-Pacific region entered the GFC under favorable economic conditions, with conservative bank regulators, high capital adequacy (exceeding 10% of total risk-weighted assets in most economies), and low and declining non-performing loan ratios across the region (Filardo et al., 2010). The economic and financial conditions are likely behind the observed pattern. Further, larger banks are more likely to survive before the GFC,

[8] The specification with interacted terms is affected by collinearity, so some coefficients are missing since some variables are dropped.

but during the GFC bank size is linked to a decline in survival probability. Large banks tend to have lower capital ratios, less stable funding, and more exposure to potentially risky market-based activities (Laeven at al. 2016). Hence, when times are good (pre-GFC), large banks are likely to be able to reap the benefits of economies of scale, while during bad times (GFC) large banks have an unfavorable mix of bank characteristics with respect to survival. Finally, a better economic situation represented by GDP growth is associated with improved survival probability during the pre-GFC period. This sensible outcome cannot be compared with other periods due to the statistical insignificance of the coefficients, though.

Regional variation. Based on the BMA procedure, three regions were selected as potential sources of heterogeneity in primary studies: Eastern Europe and the former Soviet Union, the Asia-Pacific region, and Latin America. For banks in Latin America, statistical insignificance precludes making inferences. For banks in the Asia-Pacific region there is weak evidence of increased survival probability. On the other hand, decreased survival probability is shown for banks in Eastern Europe and the former Soviet Union (Tables 5 and 6). This result resonates well with the fact that the transformation process in these countries initially involved the break-up of the mono-bank system, the privatization of spun-off banks, the formation of new private banks, and entry into the market by foreign banks at a later stage of transformation (Bonin et al., 2015). In this respect, the banking sector in Eastern Europe and the former Soviet Union lagged behind for some time in terms of its structure, competitiveness, and progress in its reform (Bonin et al., 2015). In any event, the results for regional coverage indicate that differences in countries can be linked to differences in the impact of CAMELS variables on bank survival.

Data and estimation techniques. Estimates based on panel data provide very small but conflicting effects, depending on the estimator employed. The evidence on the systematic link between estimation techniques and results is rather mixed. The results (Tables 5 and 6) indicate that Cox proportional hazards estimation tends to deliver a small negative impact on bank survival, while the econometrically less reliable OLS estimation produces a larger positive impact (Tables 5 and 6). The use of time and industry fixed effects delivers small positive effects. This result indicates that analytical approaches that aim to deal with endogeneity probably deliver estimates that are somewhat larger than they would be otherwise. Finally, the precision of the studies proxied by the standard errors of the PCCs produces a significant, economically sizeable, and positive effect (Tables 5 and 6). Hence, standard error is a variable that is quite important to explain variation in the estimates. The finding that large standard errors are associated with large estimates constitutes a violation of the mutual independence of standard errors and estimates, which is conventionally assumed in estimation methods. This violation of independence hints at a preference to report large estimates. This finding resonates well with the already-established presence of publication selection bias in primary studies.

In sum, the key message from the MRA results reported above is that, if other study conditions are equal, there is no statistically significant difference among the CAMELS variables (Table 5) or among almost all determinants (Table 6) with respect to the probability of bank survival. In other words, the predictive power of these variables is almost equal and extremely small. In this sense, the MRA results are highly consistent with the meta-synthesis results reported in Table 2 and Figure 2. Furthermore, the reported estimates are strongly influenced by other study conditions (region, estimation period, empirical approach, etc.). In the next section, we explore further issues that might affect the MRA results.

7 Discussion

7.1 Differences among models

Despite accounting for heterogeneity in primary studies, the CAMELS variables do not exhibit economically meaningful impact on bank survival/failure according to the findings. Still, we proceed with several further steps as a robustness check. We perform simple meta-analyses on subsets of the CAMELS proxies where the regression coefficients are comparable in terms of having the same independent and dependent variables and using the same family of survival models. With this distinction we strive to look as directly as possible at the economic effect of CAMELS variables.

The models used in primary studies can be divided into five categories: logit/probit models, Cox proportional hazards models, parametric hazards models, other hazards models, and other models (none of the other four). The first two categories produce most of the estimates we analyze. Logit/probit models in primary studies use failure probability as a dependent variable and the standard set of CAMELS variables as independent variables. The Cox proportional hazards model (Cox, 1972) belongs to a family of survival models that uses time-to-failure as an observable dependent variable and CAMELS variables as independent variables. Survival models bypass the necessity of proxies to capture bank failure risk, which might preclude accurate comparison with other models. An advantage of survival models is that, compared to standard logit models, they allow for the probability of bank failure to vary over time. While parametric hazards models depend on the specification of a hazard function, the Cox proportional hazards model does not require assumptions on the baseline hazard function and the results do not suffer from incorrect assumption bias (Pappas et al., 2017).

We present the results obtained from estimates based on the above model categories in Table 7. The key message from this table is that the logit/probit model exhibits a positive effect of CAMELS variables on bank survival, while the Cox proportional hazards model (along with other hazards models) exhibits a negative effect. However, in both cases the impact is so small that it is economically meaningless. Parametric hazards models produce statistically insignificant results, which might hint at the presence of a bias due to incorrect assumptions on the baseline hazard function that affect estimates. Models outside of the four principle categories deliver a positive and very negligible impact, but the result should be taken cautiously as it is based on a small number of estimates.

The values of a traditional synthesis as well as estimates that are based on the UWLS show that impacts of CAMELS variables are slightly different across model types, but they uniformly show that the effect size of CAMELS variables is very small and insignificant in an economic sense. We take this outcome as a robustness exercise confirming the finding (based on the MRA study above) that CAMELS variables do not have an economic effect on bank survival/failure.

7.2 Best practice estimation

The results of our multiple meta-regression models reported in Tables 5 and 6 confirm that the effect of CAMELS variables on bank survival/failure is almost non-existent. In order to minimize the impact of various biases present in the primary studies, we substitute realistically sensible values for the MRA independent variables in order to summarize our multiple MRA findings into one single estimate similar to Havránek (2015) and de Linde Leonard and Stanley (2020).

Since no publication selection bias is an ideal condition for empirical assessment, we first set SE equal to zero. As SE likely represents publication-selection bias, this constraint enables us to observe the impact of CAMELS without publication-selection bias. Second, we define the best research practice that minimizes other types of potential biases. Although best practice might be a subjective concept, we strive to minimize subjective choices and proceed in a manner found in other meta-analyses. For this analysis, two key issues are linked to the best research practice: primary analyses should (i) analyze panel data and (ii) estimate a model by using a non-OLS estimator. We control for these conditions by setting a value of 1 for meta-independent variable panel data and a value of 0 for meta-independent variable OLS. Because we performed a BMA analysis, we include only the BMA-selected variables, which helps us avoid omitted-variable bias by definition. We set these variables to their sample means. Furthermore, our previous results show that studies that controlled for location, time and industry fixed effects find a larger effect size, so we set a value of 1 for these characteristics.

We also make the following choice with respect to empirical models used in primary studies. In hazards models, survival/failure probability is regressed on the “initial conditions” prevalent at the beginning of the researched period. With logit/probit models researchers that use panel data examine the impact of various factors on bank survival/failure probability during specific time periods in a more direct way; logit/probit models also produce a majority of the estimates we meta-analyze. Therefore, we choose a best practice estimation with a panel logit/probit model with controls for time fixed effects, location fixed effects, and industry fixed effects with no publication selection bias.

We present the results of the best practice estimation in Table 8. Two sets of results (Table 8, panel a and b) are based on the cluster-robust WLS estimates and the cluster-robust random-effects (RE) panel GLS estimates derived in our MRA that are reported in Tables 5 and 6, respectively.

The coefficients of all CAMELS variables (Table 8, panel a) are statistically significant, and the values produced by the WLS estimator are higher than the synthesized values reported in Table 2. Still, the potential impact of specific CAMELS variables on bank survival ranges between 0.018 and 0.044; therefore, it is negligible by all standards. Estimates from the RE GLS estimator provide a somewhat different outcome, though. They show that the effects of specific CAMELS variables range between 0.11 (Management) and 0.18 (Sensitivity). Thus, for an increase in Sensitivity (to market risk) by one unit we can expect the link to the probability of bank survival to increase by 0.18 units. Results obtained with the RE GLS estimator are of an order of magnitude larger than those with the WLS estimator. However, the economic significance of the impact of the CAMELS variables can still be characterized as small at best.

The effects of moderators selected via the BMA procedure (Table 8, panel b) are uniformly negligible across both types of estimator. Despite the statistical significance, the economic impact of these coefficients is next to nonexistent. A single exception that merits a note is interest rate: for an increase in interest rate by one unit we can expect the link to probability of bank survival to decrease by 0.09 units. This impact places interest rate in the vicinity of the weakest impact of Management in the CAMELS group. Otherwise, no other economic variable produces any economically sensible effect.

The results of the MRA presented in Section 6 showed that there is no link between CAMELS variables and the probability of bank survival. The same was found in the case of (macro)economic variables and bank- and market-specific characteristics. In order to rule out several causes of limitations that might produce such a result, we performed a best practice estimation showing that with the exception of the estimates of CAMELS variables computed using Model [2] in Table 8, panel a, the best practice estimation does not produce a significantly larger effect size of CAMELS variables or other factors relevant to bank survival. We believe the outcome of the best practice estimation delivers a clear pattern that is free from the influence of inadequate estimation approach, publication selection bias, and inappropriate variable choice (as this step is circumvented via the BMA).

8 Conclusions

In this study, we perform a meta-analysis to summarize and assess the diverse research literature on the impact of CAMELS ratings on bank survival. The empirical effects of the ratings are surprisingly varied. The association of CAMELS ratings with the probability of bank survival ranges across extreme values, from -0.8 to +0.8, while the bulk of the distribution hovers over the (-0.2; +0.25) interval. The meta-synthesis resulted in the CAMELS variables having a negligible effect (Table 2). The MRA-based evidence also shows no economic impact of the CAMELS variables (Table 5). Effects of bank-specific, (macro)economic, and market factors is absent as well (Table 6). We also found that these findings are not strongly influenced by differences in empirical models (Table 7). In addition, the best practice approach reveals only very small economically meaningful impacts on bank survival produced by the set of CAMELS (Table 8). Finally, the evidence accounts for a publication selection bias present in primary studies (Table 3 and Table A2 in the Appendix).

Our results undermine the generally accepted view that CAMELS variables are effective indicators of the probability of bank survival or failure. Why are the effects of these variables so small? First, the CAMELS supervisory rating system was developed to provide a summary of bank conditions at the time of an exam and not as a tool to assess or to quantify bank failure or survival probabilities. The use of CAMELS to serve as determinants of the future success of a bank might be a faulty research choice in the first place. Second, researchers do not actually use the CAMELS variables themselves because they are not available to the public. Instead, researchers employ various proxies. Although the proxies sensibly describe aspects of the standing of a bank, there is no guarantee that proxies reflect the CAMELS rating system accurately. Both of these issues can influence the size of an impact or even if the impact exists at all. This study, of course, does not propose a solution to these two issues.

In sum, the effect of CAMELS on the probability of bank survival is either absent or quite small in an economic sense. Hence, researchers should be cautious with expectations of the strength of CAMELS variables as predictors of bank survival. The findings also imply that policy makers might find it difficult to reliably track problematic banks when relying on CAMELS variables alone.

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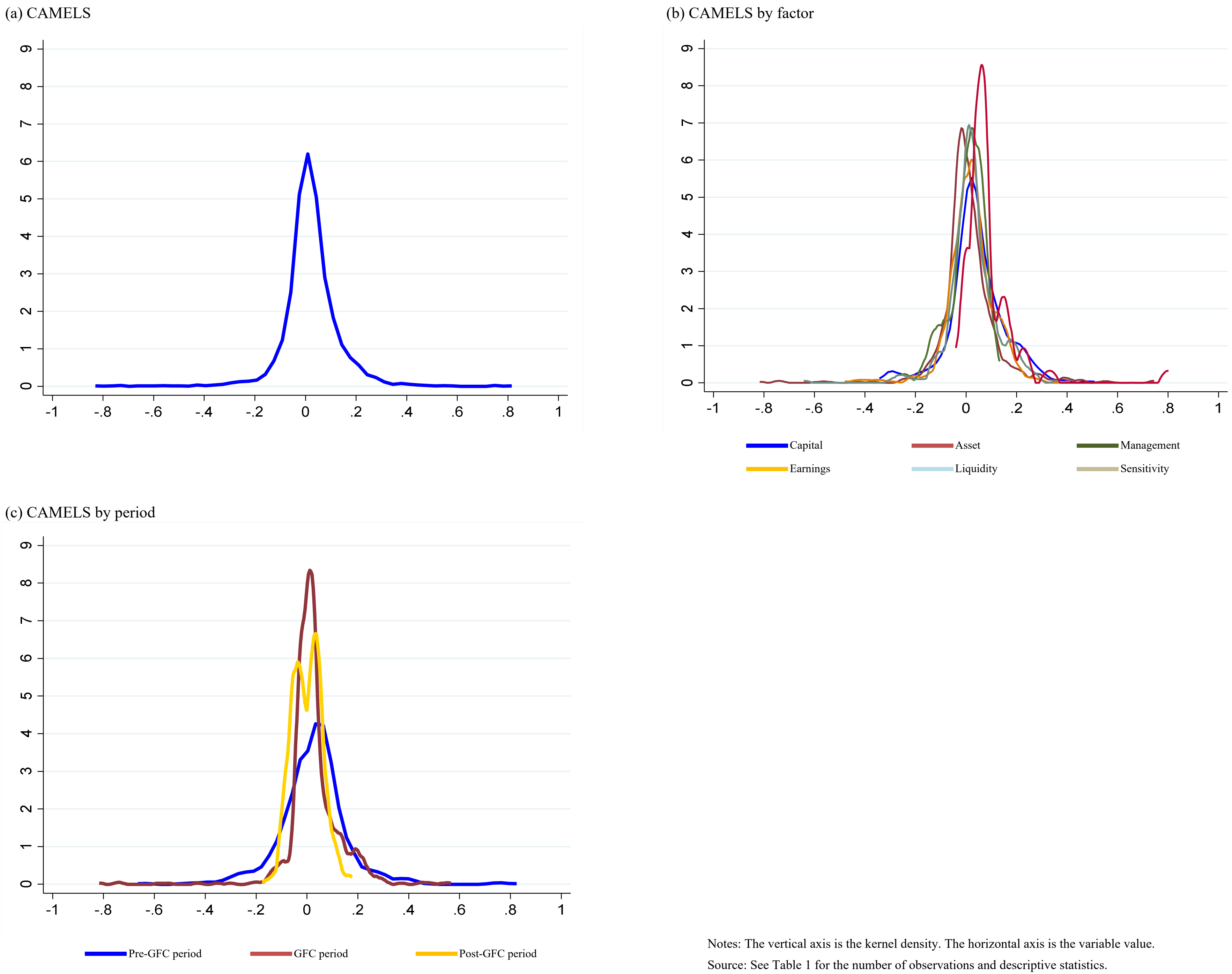
Table 1. Descriptive statistics of the partial correlation coefficients and Shapiro–Wilk normality test of collected estimates

Variable type	K	Mean	Median	S.D.	Max.	Min.	Kurtosis	Skewness	Shapiro-Wilk normality test (z)
CAMELS	2120	0.023	0.017	0.108	0.802	-0.817	13.328	-0.083	12.794 ***
Capital	374	0.042	0.033	0.113	0.488	-0.321	4.939	-0.109	5.900 ***
Asset	771	0.012	0.000	0.119	0.745	-0.817	16.401	0.001	11.306 ***
Management	141	0.003	0.014	0.071	0.133	-0.255	4.217	-1.042	4.551 ***
Earnings	412	0.020	0.019	0.094	0.414	-0.481	8.294	-0.830	7.475 ***
Liquidity	366	0.027	0.020	0.096	0.366	-0.643	10.155	-0.792	7.283 ***
Sensitivity	56	0.089	0.062	0.120	0.802	-0.040	23.968	4.041	6.408 ***
Pre-GFC period	791	0.026	0.030	0.130	0.802	-0.643	8.277	0.380	8.627 ***
GFC period	1040	0.027	0.014	0.099	0.566	-0.817	19.681	-1.065	12.109 ***
Post-GFC period	289	0.000	0.004	0.058	0.177	-0.177	2.893	0.149	2.501 ***
Firm size	243	0.006	-0.001	0.081	0.357	-0.337	7.409	0.540	6.829 ***
Listed on stock exchange	46	-0.018	-0.027	0.056	0.144	-0.160	4.888	0.466	3.319 ***
Firm age	47	-0.050	-0.050	0.066	0.149	-0.234	3.954	0.148	1.143
Foreign ownership	36	-0.012	-0.033	0.066	0.150	-0.076	4.711	1.776	5.105 ***
Market concentration	43	-0.010	0.015	0.057	0.051	-0.190	5.375	-1.526	4.042 ***
GDP growth	130	0.000	-0.003	0.087	0.468	-0.177	9.093	1.590	5.309 ***
Inflation	101	-0.025	0.018	0.097	0.209	-0.273	3.235	-0.853	4.696 ***
Interest rate	74	-0.088	-0.025	0.139	0.163	-0.364	2.118	-0.580	3.933 ***
Stock market volatility	57	-0.012	-0.025	0.061	0.063	-0.253	6.501	-1.377	4.213 ***

Notes: Shapiro-Wilk normality test tests the null hypothesis that data is normally distributed.*** denotes statistical significance at the 1%.

Figure 1. Kernel density estimation of collected estimates of CAMELS variables



Notes: The vertical axis is the kernel density. The horizontal axis is the variable value.

Source: See Table 1 for the number of observations and descriptive statistics.

Table 2. Synthesis of estimates

Variable type	Number of estimates (K)	(a) Traditional synthesis: Fixed-effect model (z value)[a]	(a) Traditional synthesis: Random-effects model (z value)[a]	(b) Heterogeneity test and measures: Cochran Q test of homogeneity (p value)[b]	(b) I^2 statistic[c]	(b) H^2 statistic[d]	(c) Unrestricted weighted least squares average (UWA): UWA of all estimates (t value)[a e]	(c) Number of the adequately powered estimates[f]	(c) WAAP (weighted average of the adequately powered estimates) (t value)[a]	(c) Median S.E. of estimates	(c) Median statistical power
CAMELS	2120	-0.003 *** (-16.64)	**0.018** *** **(8.37)**	70950.14 *** (0.000)	99.37	158.53	-0.003 ** (-1.98)	0	- (-)	0.017	0.037
Capital	374	-0.002 *** (-6.37)	**0.038** *** **(7.54)**	11014.12 *** (0.000)	99.57	234.2	-0.002 (-0.17)	0	- (-)	0.026	0.030
Asset	771	-0.007 *** (-25.05)	0.007 * (1.74)	47532.12 *** (0.000)	99.49	197.57	-0.007 *** (-3.02)	8	**-0.010** *** **(-9.14)**	0.013	0.077
Management	141	-0.002 *** (-5.53)	**0.005** **(1.05)**	944.55 *** (0.000)	99.23	129.18	-0.002 * (-1.69)	0	- (-)	0.033	0.028
Earnings	412	0.004 *** (6.96)	**0.014** *** **(3.82)**	4209.97 *** (0.000)	97.39	38.37	0.004 * (1.95)	0	- (-)	0.024	0.036
Liquidity	366	0.002 *** (3.76)	**0.019** *** **(4.64)**	3692.90 *** (0.000)	97.10	34.47	0.002 (1.15)	0	- (-)	0.020	0.032
Sensitivity	56	0.023 *** (12.16)	0.086 *** (4.84)	2924.30 *** (0.000)	98.38	61.88	0.023 * (1.71)	3	**0.006** **(2.09)**	0.054	0.063
Pre-GFC period	791	-0.005 *** (-26.04)	0.022 *** (5.18)	18239.12 *** (0.000)	99.77	433.47	-0.005 *** (-4.39)	24	**-0.007** *** **(-7.73)**	0.040	0.033
GFC period	1040	0.006 *** (17.08)	**0.021** *** **(7.27)**	48257.59 *** (0.000)	98.61	71.75	0.006 ** (2.51)	0	- (-)	0.013	0.064
Post-GFC period	289	-0.009 *** (-12.35)	**-0.006** ** **(-2.05)**	3608.17 *** (0.000)	93.33	14.99	-0.009 *** (-3.23)	0	- (-)	0.029	0.048
Firm size	243	-0.005 *** (-14.98)	0.002 (0.55)	2900.11 *** (0.000)	99.05	105.1	-0.005 *** (-4.16)	8	**-0.004** *** **(-9.03)**	0.014	0.054
Listed on stock exchange	46	-0.028 *** (-16.24)	-0.019 *** (-3.20)	286.44 *** (0.000)	90.75	10.81	-0.028 *** (-6.45)	3	**-0.023** ** **(-7.44)**	0.012	0.645
Firm age	47	-0.021 *** (-15.45)	-0.049 *** (-5.09)	2691.07 *** (0.000)	97.81	45.68	-0.021 (-2.31)	9	**0.027** **(1.45)**	0.010	0.567
Foreign ownership	36	-0.030 *** (-15.68)	-0.032 *** (-7.99)	154.26 *** (0.000)	70.06	3.34	-0.030 *** (-7.61)	16	**-0.030** *** **(-6.45)**	0.013	0.683
Market concentration	43	0.003 (1.24)	**-0.008** **(-1.01)**	319.17 *** (0.000)	92.08	12.63	0.003 (0.38)	0	- (-)	0.016	0.037
GDP growth	130	-0.004 *** (-8.77)	0.0003 (0.04)	2123.48 *** (0.000)	99.42	171.47	-0.004 ** (-2.00)	4	**-0.003** ** **(-4.64)**	0.033	0.033
Inflation	101	0.010 *** (4.99)	**-0.016** * **(-1.88)**	554.21 *** (0.000)	93.49	15.36	0.010 ** (2.21)	0	- (-)	0.034	0.049
Interest rate	74	-0.009 *** (-4.28)	**-0.085** *** **(-5.40)**	881.77 *** (0.000)	98.07	51.82	-0.009 (-1.14)	0	- (-)	0.036	0.042
Stock market volatility	57	0.026 *** (10.90)	**0.005** **(0.83)**	193.30 *** (0.000)	77.62	4.47	0.026 *** (6.02)	0	- (-)	0.034	0.117

Notes: *** and ** denote statistical significance at the 1% and 5% level, respectively. Selected synthesis values are emphasized in bold.

[a] Null hypothesis: The synthesized effect size is zero.

[b] Null hypothesis: Effect sizes are homogeneous.

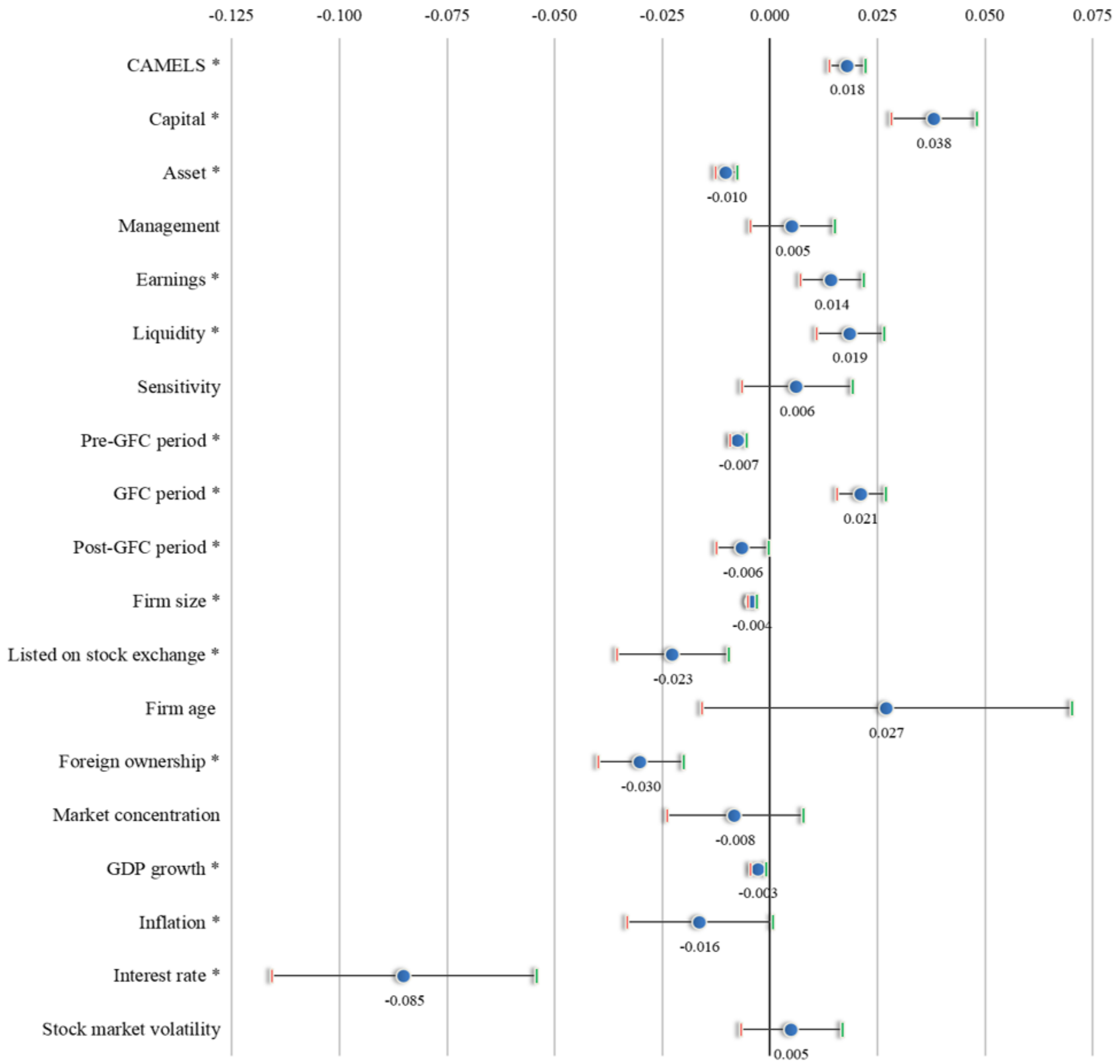
[c] Ranges between 0 and 100% with larger scores indicating heterogeneity.

[d] Takes zero in the case of homogeneity

[e] Synthesis method advocated by Stanley and Doucouliagos (2017) and Stanley et al. (2017)

[f] Denotes number of estimates with statistical power of 0.80 or more which is computed referring to the UWA of all collected estimates.

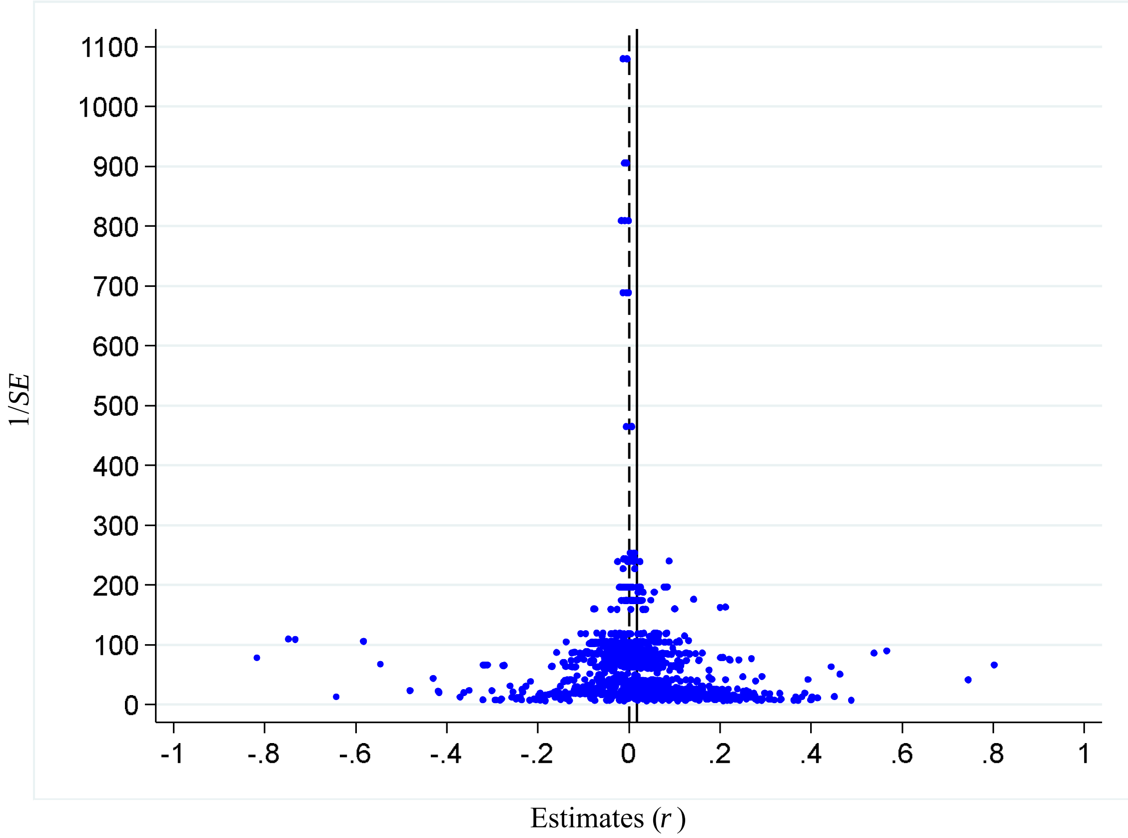
Figure 2. Illustrated comparison of selected synthesis values



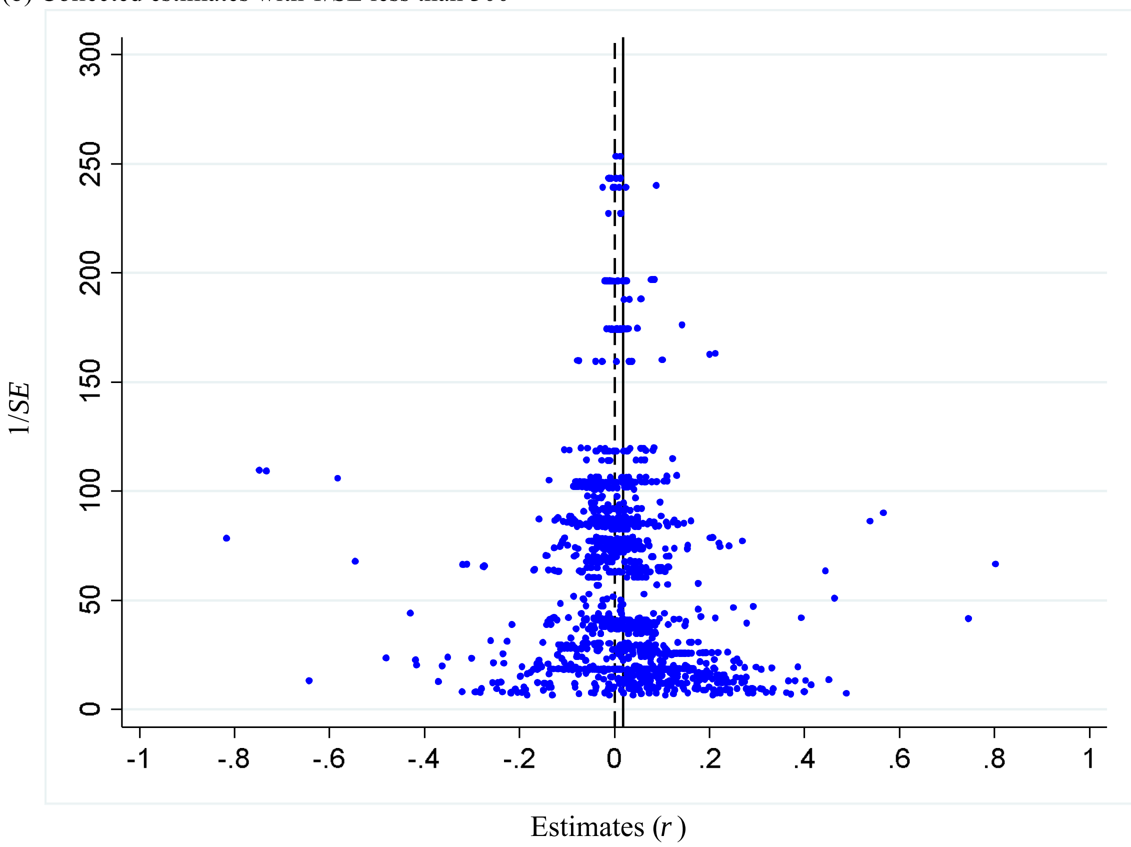
Notes: The ● mark displays the synthesis value selected in Table 2 (emphasized in bold). The left and right adjacent lines illustrate its 95% confidence interval. The synthesiss values of the variables with asterisk (*) are statistically significant.

Figure 3. Funnel plot of partial correlation coefficients of CAMELS variables

(a) All collected estimates



(b) Collected estimates with 1/SE less than 300



Note: The solid line indicates the selected synthesis value reported in Table 2.

Table 3. Meta-regression analysis of publication selection bias: CAMELS variables

(a) FAT (publication selection bias) – PET (genuine effect) test

Estimator	Unrestricted WLS	Cluster-robust unrestricted WLS	Cluster-robust random-effects panel GLS
Model	[1]	[2]	[3] [a]
β_1 (PET)	-0.0062 ***	-0.0062 ***	-0.0053 *
	(0.001)	(0.002)	(0.003)
β_0 (FAT)	0.8806 ***	0.8806 ***	1.0341 *
	(0.125)	(0.291)	(0.281)
K	2120	2120	2120
R^2	0.016	0.016	0.011

(b) PEESE approach for estimation of publication-selection-bias-adjusted effect size

Estimator	Unrestricted WLS	Cluster-robust unrestricted WLS	Random-effects panel ML
Model	[4]	[5]	[6]
γ_1 (PEESE)	-0.0034 ***	-0.0034	-0.0023
	(0.001)	(-0.003)	(0.002)
γ_0	14.6485 ***	14.6485 ***	10.0278 *
	(1.299)	(3.613)	(5.445)
K	2120	2120	2120
R^2	0.011	0.011	-

Notes: Figures in parentheses beneath the regression coefficients are standard errors. Models [2], [3], and [5] report standard errors clustered by study. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] Hausman test: $\chi^2 = 0.39$, $p = 0.5308$

Table 4. Bayesian model averaging analysis of model uncertainty

(a) Estimation using collected estimates of CAMELS variables

Moderator	Coef.	S.E.	*t* value	PIP
Focus regressors				
Asset	-0.01682	0.00652	-2.58	1.00
Management	-0.03567	0.01016	-3.51	1.00
Earnings	-0.01472	0.00738	-1.99	1.00
Liquidity	-0.00593	0.00753	-0.79	1.00
Sensitivity	0.02828	0.01520	1.86	1.00
GFC period	-0.01278	0.00796	-1.60	1.00
Post-GFC period	-0.03662	0.01077	-3.40	1.00
S.E.	0.98445	0.09781	10.06	1.00
Auxiliary regressors				
Worldwide	0.00004	0.00134	0.03	0.02
Advanced countries	-0.00038	0.00380	-0.10	0.03
Developing countries	0.00001	0.00352	0.00	0.02
EU and Western Europe	-0.00157	0.00497	-0.32	0.12
Eastern Europe and the former Soviet Union	-0.05785	0.01179	-4.91	1.00
Asia Pacific	-0.02985	0.01296	-2.30	0.91
Africa	-0.00296	0.01469	-0.20	0.06
Latin America	-0.07884	0.01402	-5.62	1.00
Islamic banks	0.00015	0.00209	0.07	0.02
Panel data	0.02540	0.00578	4.39	1.00
OLS	0.00976	0.01966	0.50	0.24
Tobit	0.02259	0.04268	0.53	0.26
Cox proportional hazards	-0.05550	0.00952	-5.83	1.00
Parametric hazards	-0.00030	0.00247	-0.12	0.03
Other estimators	-0.00108	0.00430	-0.25	0.08
Location fixed effects	-0.00064	0.00706	-0.09	0.07
Time fixed effects	0.03333	0.01054	3.16	0.98
Industry fixed effects	0.08989	0.02035	4.42	1.00
Lagged variable	0.00013	0.00127	0.10	0.03
With an interaction term(s)	0.00207	0.01054	0.20	0.06
K		2120		
Model space		1,048,576		

(b) Estimation using all collected estimates

Moderator	Coef.	S.E.	*t* value	PIP
Focus regressors				
Firm size	-0.01651	0.00679	-2.43	1.00
Listed on stock exchange	-0.00370	0.01542	-0.24	1.00
Firm age	-0.02770	0.01515	-1.83	1.00
Foreign ownership	0.01187	0.01768	0.67	1.00
Market concentration	-0.03989	0.01614	-2.47	1.00
GDP growth	-0.03569	0.00931	-3.83	1.00
Inflation	-0.05352	0.01030	-5.20	1.00
Interest rate	-0.12377	0.01265	-9.78	1.00
Stock market volatility	-0.05041	0.01379	-3.65	1.00
S.E.	0.67129	0.09795	6.85	1.00
Auxiliary regressors				
Average estimation year	-0.00061	0.00063	-0.97	0.54
Worldwide	0.01319	0.01217	1.08	0.60
Advanced countries	-0.00063	0.00413	-0.15	0.04
Developing countries	-0.00008	0.00263	-0.03	0.02
EU and Western Europe	0.00003	0.00120	0.02	0.03
Eastern Europe and the former Soviet Union	-0.02808	0.01490	-1.88	0.90
Asia Pacific	-0.02075	0.01230	-1.69	0.81
Africa	-0.00185	0.01139	-0.16	0.04
Latin America	-0.03723	0.02049	-1.82	0.84
Islamic banks	0.00499	0.01121	0.44	0.20
Panel data	0.01210	0.00748	1.62	0.79
OLS	0.08457	0.01521	5.56	1.00
Tobit	0.04739	0.04056	1.17	0.64
Cox proportional hazards	-0.04294	0.01072	-4.00	1.00
Parametric hazards	-0.00137	0.00525	-0.26	0.09
Other estimators	-0.00022	0.00183	-0.12	0.03
Location fixed effects	0.02191	0.01725	1.27	0.65
Time fixed effects	0.01268	0.01717	0.74	0.38
Industry fixed effects	0.02063	0.02649	0.78	0.43
Lagged variable	-0.00005	0.00106	-0.05	0.03
With an interaction term(s)	0.00157	0.00837	0.19	0.05
K		2897		
Model space		2,097,152		

Notes: S.E. and PIP denote standard errors and posterior inclusion probability, respectively. The variables of asset, management, earnings, liquidity, sensitivity, GFC period, post-GFC period in Panel A, and firm size, listed on stock exchange, firm age, foreign ownership, market concentration, GDP growth, inflation, interest rate, and stock market volatility in Panel B as well as standard errors of partial correlation coefficients are included in the estimation as focus regressors. Therefore, the PIP of these key variables is 1.00.
Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.

Table 5. Meta-regression analysis of literature heterogeneity: Focus on CAMELS variables

Estimator (analytical weight in brackets) [a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Study size]	Cluster-robust random-effects panel GLS [b]
Meta-independent variable (default study type)/model	[1]	[2]	[3]
Variable type (Capital)			
Asset	-0.0049	-0.0025	-0.0183
	(0.005)	(0.004)	(0.015)
Management	0.0046 *	0.0050 **	-0.0398 **
	(0.003)	(0.002)	(0.020)
Earnings	-0.0004	0.0022	-0.0175
	(0.006)	(0.004)	(0.016)
Liquidity	-0.0035	-0.0042	-0.0116
	(0.009)	(0.009)	(0.016)
Sensitivity	0.0151	0.0137	0.0257
	(0.020)	(0.019)	(0.018)
Estimation period (Pre-GFC period)			
GFC period	-0.0097	-0.0106	-0.0144
	(0.007)	(0.007)	(0.016)
Post-GFC period	0.0022	0.0143	-0.0416 **
	(0.013)	(0.013)	(0.018)
Selected moderators			
Eastern Europe and the former Soviet Union	-0.0246	-0.0346 **	-0.0464 ***
	(0.015)	(0.016)	(0.018)
Asia Pacific	-0.0016	0.0057	-0.0143
	(0.019)	(0.023)	(0.013)
Latin America	-0.0270	-0.0560	-0.0492
	(0.036)	(0.055)	(0.040)
Panel data	0.0006	-0.0118 *	0.0224 **
	(0.006)	(0.006)	(0.011)
Cox proportional hazards	-0.0382 **	-0.0504 ***	-0.0668 **
	(0.015)	(0.018)	(0.031)
Time fixed effects	0.0193	0.0218	0.0348 *
	(0.012)	(0.017)	(0.018)
Industry fixed effects	0.0017	0.0003	0.0901 **
	(0.023)	(0.031)	(0.038)
Standard error of partial correlation coefficient			
S.E.	0.7122 *	0.6236	0.5537 *
	(0.383)	(0.483)	(0.301)
Constant	0.0106	0.0196 ***	0.0312 *
	(0.008)	(0.007)	(0.017)
K	2120	2120	2120
R^2	0.074	0.082	0.130

Notes: Selected moderators denote the meta-independent variables having a PIP of 0.80 or more in the Bayesian model averaging estimation reported in Panel (a) of Appendix Table A3. Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] Precision: inverse of squared standard error; Study size: inverse of number of reported estimates multiplied by precis

[b] Hausman test: $\chi^2 = 9.77$, $p = 0.6360$

Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.

Table 6. Meta-regression analysis of literature heterogeneity: Comparison of CAMELS with other firm- and country-level factors

Estimator (analytical weight in brackets) [a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Study size]	Cluster-robust random-effects panel GLS [b]
Meta-independent variable (default study type)/model	[1]	[2]	[3]
Variable type (CAMELS)			
Firm size	0.0004	0.0009	-0.0232
	(0.003)	(0.003)	(0.019)
Listed on stock exchange	-0.0177 *	-0.0233 ***	-0.0049
	(0.009)	(0.008)	(0.014)
Firm age	-0.0163	0.0738 *	-0.0321
	(0.024)	(0.041)	(0.024)
Foreign ownership	-0.0171 **	-0.0188 ***	-0.0021
	(0.007)	(0.003)	(0.014)
Market concentration	-0.0017	-0.0009	-0.0456 **
	(0.009)	(0.013)	(0.021)
GDP growth	0.0021	0.0045 ***	-0.0393 *
	(0.004)	(0.002)	(0.022)
Inflation	0.0060	-0.0044	-0.0465
	(0.012)	(0.012)	(0.034)
Interest rate	-0.0159	-0.0239	-0.1157 **
	(0.019)	(0.017)	(0.059)
Stock market volatility	0.0191	0.0162	-0.0393 ***
	(0.017)	(0.015)	(0.009)
Selected moderators			
Eastern Europe and the former Soviet Union	-0.0146	-0.0098	-0.0207 **
	(0.011)	(0.009)	(0.008)
Asia Pacific	0.0071	0.0329 *	-0.0034
	(0.024)	(0.019)	(0.009)
Latin America	0.0384	0.0024	-0.0345
	(0.032)	(0.047)	(0.030)
OLS	0.1592 ***	0.1546 ***	0.0861 ***
	(0.009)	(0.009)	(0.008)
Cox proportional hazards	-0.0149 ***	-0.0189 ***	-0.0490 *
	(0.003)	(0.005)	(0.027)
Standard error of partial correlation coefficient			
S.E.	-0.0326	-0.0086	0.2993 ***
	(0.342)	(0.401)	(0.115)
Constant	0.0076 **	0.0114 **	0.0245 ***
	(0.003)	(0.005)	(0.009)
K	2897	2897	2897
R^2	0.059	0.102	0.102

Notes: Selected moderators denote the meta-independent variables having a PIP of 0.80 or more in the Bayesian model averaging estimation reported in Panel (b) of Appendix Table A3. Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] Precision: inverse of squared standard error; Study size: inverse of number of reported estimates multiplied by precis

[b] Hausman test: $\chi^2 = 5.28$, $p = 0.9685$

Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.

Table 7. Synthesis of estimates of CAMELS variables by empirical model type

Empirical model type	Number of estimates (K)	(a) Traditional synthesis: Fixed-effect model (z value)[a]	(a) Traditional synthesis: Random-effects model (z value)[a]	(b) Heterogeneity test and measures: Cochrane Q test of homogeneity (p value)[b]	(b) I^2 statistic[c]	(b) H^2 statistic[d]	(c) Unrestricted weighted least squares average (UWA): UWA of all estimates (t value)[a e]	(c) Number of the adequately powered estimates[f]	(c) WAAP (weighted average of the adequately powered estimates) (t value)[a]	(c) Median S.E. of estimates	(c) Median statistical power
Logit/probit model of failure probability	1365	0.008 *** (25.38)	0.026 *** (9.80)	47297.93 *** (0.000)	98.48	65.78	0.008 *** (4.22)	6	**0.004** **(2.00)**	0.024	0.051
Cox proportional hazards model	294	-0.009 *** (-45.17)	-0.030 *** (-5.62)	11995.23 *** (0.000)	99.84	635.26	-0.009 *** (-6.63)	24	**-0.007** *** **(-7.73)**	0.015	0.090
Parametric hazards model	171	-0.0005 (-0.27)	**0.031** *** **(5.05)**	1228.71 *** (0.000)	88.78	88.78	-0.0005 (-0.40)	0	- (-)	0.054	0.026
Other hazards models	206	0.010 *** (15.17)	**0.008** **(1.61)**	3464.77 *** (0.000)	98.10	52.71	0.010 *** (3.70)	0	- (-)	0.013	0.115
Models other than above	84	0.017 *** (17.72)	0.058 *** (3.90)	4011.72 *** (0.000)	99.54	218.46	0.017 ** (2.58)	36	**0.012** ** **(2.67)**	0.025	0.102

Notes: *** and ** denote statistical significance at the 1% and 5% level, respectively. Selected synthesis values are emphasized in bold.

[a] Null hypothesis: The synthesized effect size is zero.

[b] Null hypothesis: Effect sizes are homogeneous.

[c] Ranges between 0 and 100% with larger scores indicating heterogeneity.

[d] Takes zero in the case of homogeneity

[e] Synthesis method advocated by Stanley and Doucouliagos (2017) and Stanley et al. (2017)

[f] Denotes number of estimates with statistical power of 0.80 or more which is computed referring to the UWA of all collected estimates.

Table 8. Best practice estimates

(a) Estimation using multiple meta-regression results reported in Column [1] and [3] of Table 5

Variable type	Number of estimates (K)	[1] Cluster-robust WLS [Precision]			[2] Cluster-robust random-effects panel GLS		
		Estimate (t value)	[95% confidence interval]		Estimate (t value)	[95% confidence interval]	
CAMELS	2120	0.0215 *** (102.84)	0.0211	0.0219	0.1281 *** (222.92)	0.1269	0.1292
Capital	374	0.0241 *** (54.47)	0.0233	0.0250	0.1464 *** (157.15)	0.1445	0.1482
Asset	771	0.0189 *** (70.02)	0.0184	0.0194	0.1235 *** (186.38)	0.1222	0.1248
Management	141	0.0297 *** (39.86)	0.0282	0.0312	0.1112 *** (85.85)	0.1086	0.1137
Earnings	412	0.0217 *** (50.25)	0.0208	0.0225	0.1200 *** (77.01)	0.1169	0.1231
Liquidity	366	0.0175 *** (36.46)	0.0166	0.0184	0.1267 *** (85.95)	0.1238	0.1296
Sensitivity	56	0.0442 *** (98.16)	0.0433	0.0451	0.1798 *** (117.39)	0.1767	0.1829

(b) Estimation using multiple meta-regression results reported in Column [1] and [3] of Table 6

Variable type	Number of estimates (K)	[1] Cluster-robust WLS [Precision]			[2] Cluster-robust random-effects panel GLS		
		Estimate (t value)	[95% confidence interval]		Estimate (t value)	[95% confidence interval]	
CAMELS	2120	0.0083 *** (39.80)	0.0079	0.0087	0.0203 *** (102.50)	0.0199	0.0206
Firm size	243	0.0069 *** (12.94)	0.0059	0.0080	-0.0028 *** (-5.02)	-0.0040	-0.0017
Listed on stock exchange	46	-0.0213 *** (-22.85)	-0.0232	-0.0194	0.0039 *** (2.93)	0.0012	0.0065
Firm age	47	-0.0172 *** (-16.09)	-0.0193	-0.0150	-0.0195 *** (-12.95)	-0.0226	-0.0165
Foreign ownership	36	-0.0182 *** (-8.06)	-0.0227	-0.0136	0.0041 *** (3.00)	0.0013	0.0069
Market concentration	43	0.0050 *** (6.84)	0.0036	0.0065	-0.0232 *** (-25.11)	-0.0251	-0.0214
GDP growth	130	0.0100 *** (27.81)	0.0093	0.0108	-0.0162 *** (-41.85)	-0.0170	-0.0154
Inflation	101	0.0147 *** (29.13)	0.0137	0.0157	-0.0242 *** (-49.42)	-0.0251	-0.0232
Interest rate	74	-0.0068 *** (-9.95)	-0.0082	-0.0054	-0.0941 *** (-150.00)	-0.0954	-0.0928
Stock market volatility	57	0.0257 *** (38.40)	0.0243	0.0270	-0.0172 *** (-20.38)	-0.0189	-0.0155

Note: *** denotes statistical significance at the 1% level.

Appendix Table A1. List of studies subject to meta-analysis

Author(s) (publication year)	Publication type [a]	Target region	Estimation period			Variable type															Number of collected estimates (K)
			From	To	Length	Capital	Asset	Management	Earnings	Liquidity	Sensitivity	Firm size	Listed on stock exchange	Firm age	Foreign ownership	Market concentration	GDP growth	Inflation	Interest rate	Stock market volatility	
Akhigbe et al. (2007)	J	North America	1999	2003	5	✓	✓		✓	✓	✓	✓									48
Aliyu and Yusof (2017)	J	Worldwide	1987	2014	28	✓	✓		✓	✓		✓						✓			60
Almanidis and Sickles (2016)	B	North America	2007	2010	4	✓	✓		✓	✓		✓		✓							112
Amador et al. (2013)	J	Latin America	1990	2011	22	✓			✓	✓											10
Arena (2008)	J	Asia Pacific, Latin America	1994	1999	6	✓	✓		✓	✓		✓			✓						35
Babajide et al. (2015)	J	Africa	2003	2011	9		✓		✓	✓											9
Barr et al. (1994)	J	North America	1986	1989	4	✓	✓	✓		✓											8
Berger and Bouwman (2013)	J	North America	1984	2010	27	✓	✓		✓	✓		✓			✓	✓					27
Betz et al. (2014)	J	EU/Western Europe	2000	2013	14	✓	✓	✓	✓	✓	✓						✓	✓		✓	78
Bologna (2015)	J	North America	2007	2009	3	✓	✓		✓			✓									96
Calabrese and Giudici (2015)	J	EU/Western Europe	1996	2011	16	✓	✓		✓	✓							✓	✓	✓		30
Cole and Gunther (1995)	J	North America	1986	1992	7	✓	✓	✓				✓									36
Cole and White (2012)	J	North America	2009	2009	1	✓	✓		✓			✓									330
Curry et al. (2007)	J	North America	1989	1995	7	✓	✓		✓		✓										43
Estrella et al. (2000)	J	North America	1988	1993	6	✓			✓												18
Evrensel (2008)	J	Worldwide	1980	1997	18											✓	✓	✓	✓		24
Fidrmuc and Süß (2009)	J	Eastern Europe and FSU	2006	2007	2	✓	✓	✓	✓	✓											20
Fiordelisi and Mare (2013)	J	EU/Western Europe	1997	2009	13	✓	✓	✓	✓	✓		✓					✓				30
Fu et al. (2014)	J	Asia Pacific	2003	2009	7		✓		✓			✓				✓	✓				19
Goenner (2020)	J	North America	1985	2010	26	✓	✓			✓		✓		✓							35
Gómez-Gonzalez and Kiefer (2009)	J	Latin America	1998	2001	4	✓	✓	✓	✓	✓											19
Gonzalez-Hermosillo et al. (1997)	J	Latin America	1991	1995	5	✓	✓		✓	✓		✓									53
Hsu and Liu (2019)	J	Asia Pacific	1999	2007	9	✓	✓	✓	✓	✓	✓							✓	✓		122
Jin et al. (2011)	J	North America	2007	2010	4	✓	✓					✓	✓								54
Jin et al. (2017)	J	North America	2007	2010	4	✓	✓		✓	✓		✓									40
Kerstein and Kozberg (2013)	J	North America	2007	2010	4	✓	✓		✓	✓	✓	✓									47
Kocenda and Iwasaki (2020)	J	Eastern Europe and FSU	2007	2015	9		✓		✓	✓		✓	✓	✓	✓						219
Korhonen (2020)	U	EU/Western Europe	2006	2012	7	✓	✓	✓	✓	✓		✓				✓	✓	✓	✓		138
Liang et al. (2020)	J	Asia Pacific	2002	2010	9	✓	✓		✓	✓	✓	✓									6
Lin and Yang (2016)	J	Asia Pacific	1999	2011	13	✓	✓	✓	✓	✓	✓						✓	✓	✓		120
Liu and Ngo (2014)	J	North America	1934	2012	79	✓	✓	✓				✓					✓				36
Lu and Whidbee (2016)	J	North America	2007	2011	5	✓	✓		✓	✓		✓	✓								34
Mäkinen and Solanko (2018)	J	Eastern Europe and FSU	2013	2017	5	✓	✓		✓	✓		✓									42
Mannasoo and Mayes (2009)	J	Eastern Europe and FSU	1995	2004	10	✓	✓	✓	✓	✓			✓			✓	✓	✓	✓	✓	88
Mare (2015)	J	EU/Western Europe	1993	2011	19	✓	✓	✓	✓	✓		✓									12
Markoulis et al. (2021)	J	EU/Western Europe	2008	2015	8	✓		✓	✓	✓		✓	✓				✓				142
Momparler et al. (2016)	J	EU/Western Europe	2006	2012	7	✓			✓	✓											3
Nurazi and Evans (2005)	J	Asia Pacific	1992	1998	7	✓			✓	✓											11
Ozdmir and Altinoz (2018)	J	North America	2008	2010	3	✓	✓		✓	✓		✓									19
Papanikolaou (2018)	J	North America	2003	2009	7	✓	✓	✓	✓	✓	✓	✓	✓					✓			18
Pappas et al. (2017)	J	Worldwide	1995	2010	16	✓	✓	✓	✓	✓		✓				✓	✓	✓			108
Peresetsky et al. (2011)	J	Eastern Europe and FSU	1998	2000	3	✓	✓		✓	✓		✓									34
Petropoulos et al. (2020)	J	North America	2008	2017	10	✓	✓		✓	✓											16
Shaffer (2012)	J	North America	1984	2010	27	✓	✓	✓		✓		✓									36
Trussel and Johnson (2012)	J	North America	2008	2009	2	✓	✓	✓	✓	✓											6
Vazquez and Federico (2015)	J	Worldwide	2008	2009	2	✓	✓		✓	✓		✓					✓		✓	✓	105
Wang et al. (2019)	J	Worldwide	2005	2015	11	✓	✓		✓								✓	✓		✓	224
Westgaard and Wijst (2001)	J	EU/Western Europe	1995	1999	5	✓		✓		✓		✓		✓							6
Whalen (1991)	J	North America	1987	1990	4		✓	✓	✓	✓											5
Wheelock and Wilson (2000)	J	North America	1984	1993	10	✓	✓	✓	✓	✓		✓		✓							66

Note: [a] B, J, and U denote book chapter, journal article, and unpublished maanuscript, respectively.

Appendix Table A2. Summary of publication selection bias tests

Variable type	Number of estimates (K)	Test results [a]		
		Funnel asymmetry test (FAT)	Precision-effect test (PET)	Precision-effect estimate with standard error (PEESE) [b]
CAMELS	2120	**Rejected**	**Rejected**	Not rejected
Capital	374	**Rejected**	**Rejected**	Not rejected
Asset	771	**Rejected**	**Rejected**	**Rejected (-0.0078/-0.0077)**
Management	141	**Rejected**	**Rejected**	Not rejected
Earnings	412	Not rejected	Not rejected	Not rejected
Liquidity	366	Not rejected	Not rejected	Not rejected
Sensitivity	56	**Rejected**	Not rejected	Not rejected
Pre-GFC period	791	**Rejected**	**Rejected**	**Rejected (-0.0047)**
GFC period	1040	Not rejected	Not rejected	Not rejected
Post-GFC period	289	Not rejected	Not rejected	Not rejected
Firm size	243	Not rejected	**Rejected**	**Rejected (-0.0052)**
Listed on stock exchange	46	Not rejected	**Rejected**	**Rejected (-0.0312/-0.0252)**
Firm age	47	**Rejected**	Not rejected	Not rejected
Foreign ownership	36	Not rejected	**Rejected**	**Rejected (-0.0341/-0.0155)**
Market concentration	43	Not rejected	Not rejected	Not rejected
GDP growth	130	Not rejected	**Rejected**	Not rejected
Inflation	101	Not rejected	**Rejected**	**Rejected (0.0274)**
Interest rate	74	**Rejected**	**Rejected**	Not rejected
Stock market volatility	57	**Rejected**	**Rejected**	**Rejected (0.0289/0.0314)**

Notes:
[a] The null hypothesis is rejected when more than two of three models show a statistically significant estimate. Otherwise not rejected.
[b] Figures in parentheses are PSB-adjusted estimates. If two or more estimates are reported, the left and right figures denote the minimum and maximum estimates, respectively.

Appendix Table A3. Names, definitions, and descriptive statistics of meta-independent variables

Variable name	Definition	Descriptive statistics		
		Mean	Median	S.D.
CAMELS				
Asset	1 = if variable type is asset, 0 = otherwise	0.266	0	0.442
Management	1 = if variable type is management, 0 = otherwise	0.049	0	0.215
Earnings	1 = if variable type is earnings, 0 = otherwise	0.142	0	0.349
Liquidity	1 = if variable type is liquidity, 0 = otherwise	0.126	0	0.332
Sensitivity	1 = if variable type is sensitivity, 0 = otherwise	0.019	0	0.138
Other firm-level factors of bank survival				
Firm size	1 = if variable type is firm size, 0 = otherwise	0.084	0	0.277
Listed on stock exchange	1 = if variable type is listed on stock exchenge, 0 = otherwise	0.016	0	0.125
Firm age	1 = if variable type is firm age, 0 = otherwise	0.016	0	0.126
Foreign ownership	1 = if variable type is foreign ownership, 0 = otherwise	0.012	0	0.111
Country-level factors of bank survival				
Market concentration	1 = if variable type is market concentration, 0 = otherwise	0.015	0	0.121
GDP growth	1 = if variable type is GDP growth, 0 = otherwise	0.045	0	0.207
Inflation	1 = if variable type is inflation, 0 = otherwise	0.035	0	0.183
Interest rate	1 = if variable type is interest rate, 0 = otherwise	0.026	0	0.158
Stock market volatility	1 = if variable type is stock market volatility, 0 = otherwise	0.020	0	0.139
Estimation period				
GFC period	1= if estimation period includes the GFC years, 0 = otherwise	0.466	0	0.499
Post-GFC period	1= if estimation period is limited to the post-GFC years, 0 = otherwise	0.170	0	0.376
Average estimation year	Average estimation year	2004.812	2008.5	7.448
Target region				
Worldwide	1 = if the target region is worldwide, 0 = otherwise	0.114	0	0.317
Advanced countries	1 = if the target region is advanced countries, 0 = otherwise	0.022	0	0.147
Developing countries	1 = if the target region is developing countries, 0 = otherwise	0.011	0	0.105
EU and Western Europe	1 = if the target region is the EU or Western Europe, 0 = otherwise	0.163	0	0.369
Eastern Europe and the former Soviet Unic	1 = if the target region is Eastern Europe and the former Soviet Union, 0 = otherwise	0.139	0	0.346
Asia Pacific	1 = if the target region is Asia Pacific, 0 = otherwise	0.114	0	0.318
Africa	1 = if the target region is Africa, 0 = otherwise	0.003	0	0.056
Latin America	1 = if the target region is Latin America, 0 = otherwise	0.033	0	0.179
Other study conditions				
Islamic banks	1 = if the target financial institutions are Islamic banks, 0 = otherwise	0.049	0	0.215
Panel data	1 = if panel data is used for estimation, 0 = otherwise	0.350	0	0.477
OLS	1 = if an OLS estimator is used for estimation, 0 = otherwise	0.017	0	0.128
Tobit	1 = if a Tobit estimator is used for estimation, 0 = otherwise	0.007	0	0.081
Cox proportional hazards	1 = if a Cox proportional hazards estimator is used for estimation, 0 = otherwise	0.162	0	0.368
Parametric hazards	1 = if a parametric hazards estimator is used for estimation, 0 = otherwise	0.089	0	0.285
Other estimators	1 = if an estimator other than logit, probit, and the above estimators is used for estimation, 0 = otherwise	0.094	0	0.292
Location fixed effects	1 = if the estimation simultaneously controls for location fixed effects, 0 = otherwise	0.130	0	0.337
Time fixed effects	1 = if the estimation simultaneously controls for time fixed effects, 0 = otherwise	0.138	0	0.345
Industry fixed effects	1 = if the estimation simultaneously controls for industry fixed effects, 0 = otherwise	0.076	0	0.264
Lagged variable	1 = if the estimation is conducted with a lagged independent variable, 0 = otherwise	0.246	0	0.431
With an interaction term(s)	1 = if the estimation is conducted with an interaction term(s), 0 = otherwise	0.009	0	0.096
S.E.	Standard error of partial correlation coefficient	0.031	0.017	0.028

Appendix Table 4. Meta-regression estimation of interacted terms between the variables of estimation period and selected variables; a robustness check

Estimator (analytical weight in brackets) [a]	Cluster-robust WLS [Precision]	Cluster-robust WLS [Study size]	Cluster-robust random-effects panel GLS [b]
Meta-independent variable (default study type)/model	[1]	[2]	[3]
Variable type (CAMELS)			
Firm size	0.0159	-0.0261 **	0.0310 ***
	(0.020)	(0.011)	(0.010)
Listed on stock exchange	-0.0137	-0.0197 **	0.0005
	(0.011)	(0.008)	(0.013)
Firm age	-0.0149	0.0705 *	-0.0262
	(0.022)	(0.039)	(0.021)
Foreign ownership	-0.0151	-0.0226 ***	0.0067
	(0.010)	(0.005)	(0.013)
Market concentration	-0.0062	0.0021	-0.0792
	(0.011)	(0.009)	(0.064)
GDP growth	-0.0359 ***	-0.0162	-0.0484 ***
	(0.003)	(0.054)	(0.006)
Inflation	0.0044	-0.0039	-0.0462
	(0.012)	(0.011)	(0.033)
Interest rate	-0.0173	-0.0255	-0.1166 **
	(0.020)	(0.020)	(0.058)
Stock market volatility	0.0189	0.0196	-0.0415 ***
	(0.016)	(0.015)	(0.010)
Estimation period (Pre-GFC period)			
GFC period	-0.0129 *	-0.0115	-0.0156
	(0.007)	(0.008)	(0.016)
Post-GFC period	-0.0194	-0.0181	-0.0264 *
	(0.012)	(0.013)	(0.016)
Selected moderators			
Eastern Europe and the former Soviet Union	-0.0093	-0.0107	-0.0055
	(0.011)	(0.013)	(0.013)
Asia Pacific	0.0019	0.0658 ***	0.0032 **
	(0.007)	(0.017)	(0.002)
Latin America	0.0032	-0.0292	-0.0539
	(0.035)	(0.052)	(0.034)
OLS	0.1395 ***	0.1396 ***	0.0670 ***
	(0.011)	(0.012)	(0.016)
Cox proportional hazards	-0.0254 ***	-0.0247 ***	-0.0509 *
	(0.007)	(0.008)	(0.029)
Interacted variables			
Pre-GFC period x Firm size	-0.0113	0.0305 ***	-0.0008
	(0.020)	(0.011)	(0.016)
Pre-GFC period x Market concentration			0.0533
			(0.062)
Pre-GFC period x GDP growth	0.0414 ***	0.0219	0.0439 *
	(0.004)	(0.054)	(0.023)
Pre-GFC period x Eastern Europe and the former Soviet Union	-0.0131	-0.0158	-0.0318
	(0.010)	(0.012)	(0.028)
Pre-GFC period x Asia Pacific	-0.0321	-0.0642 **	-0.0371 *
	(0.025)	(0.029)	(0.023)
Pre-GFC period x Latin America			
GFC period x Firm size	-0.0390 *		-0.0946 ***
	(0.022)		(0.026)
GFC period x Market concentration	-0.0102	-0.0779	
	(0.021)	(0.076)	
GFC period x GDP growth	-0.0067		-0.0179
	(0.041)		(0.037)
GFC period x Eastern Europe and the former Soviet Union			-0.0196
			(0.018)
GFC period x Asia Pacific	0.0613 ***		0.0605 ***
	(0.010)		(0.014)
GFC period x Latin America			
Post-GFC period x Firm size		0.0243	
		(0.019)	
Post-GFC period x Market concentration			
Post-GFC period x GDP growth		-0.0209	
		(0.056)	
Post-GFC period x Eastern Europe and the former Soviet Union	0.0043	0.0136	
	(0.022)	(0.026)	
Post-GFC period x Asia Pacific		-0.0644 ***	
		(0.015)	
Post-GFC period x Latin America			
Standard error of partial correlation coefficient			
S.E.	0.2938	0.3104	0.3155 ***
	(0.375)	(0.459)	(0.109)
Constant	0.0166 **	0.0160 *	0.0339 **
	(0.007)	(0.009)	(0.015)
K	2897	2897	2897
R^2	0.086	0.124	0.125

Notes: Selected moderators denote the meta-independent variables having a PIP of 0.80 or more in the Bayesian model averaging estimation reported in Panel (a) of Appendix Table A3. Figures in parentheses beneath the regression coefficients are robust standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

[a] Precision: inverse of squared standard error; Study size: inverse of number of reported estimates multiplied by precisior

[b] Hausman test: $\chi^2 = 3.29$, $p = 1.0000$

Source: See Table 3 for the definitions and descriptive statistics of meta-independent variables.