REVISITING THE ESTIMATION OF THE COST OF EQUITY OF EURO AREA BANKS

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Resumen

El objetivo de este artículo es estimar el coste de capital de una amplia muestra de entidades de crédito del área del euro. Con este fin, los autores consideran varias metodologías de estimación bajo dos enfoques principales: i) modelos de series temporales multifactoriales de rendimientos bursátiles, y ii) modelos de descuento de dividendos. Se observa que, a escala nacional, las estimaciones de los distintos modelos muestran una variación temporal similar, pero las diferencias en niveles pueden ser considerables. La relación entre las distintas estimaciones de coste de capital y los observables bancarios es relativamente débil. Las estimaciones de los modelos de descuento de dividendos muestran una relación algo más sólida con los fundamentos bancarios, mientras que las de los modelos de factores lo hacen más claramente solo para las entidades de mayor tamaño. Una medida combinada, construida como un promedio simple entre modelos, también muestra una asociación moderada con los fundamentos. En general, los resultados destacan las incertidumbres inherentes a la estimación del coste del capital y la importancia de considerar diferentes modelos alternativos.

Palabras clave: coste del capital, rentabilidad bancaria.

Abstract

The aim of this article is to estimate the cost of equity for a large sample of euro area banks. To this end, the authors consider several estimation methodologies falling under two main approaches: (i) multi-factor time-series models of stock market returns; and (ii) dividend discount models. It is found that, at country level, the estimates of the various models display a similar time variation, but differences in levels can be substantial. The relationship between the different cost of equity estimates and bank observables is relatively weak. Estimates from dividend discount models show a somewhat more robust relationship with bank fundamentals, while those from factor models do so more clearly only for larger banks. A combined measure built as a simple average across models also shows a moderate association with fundamentals. Overall, the results highlight the uncertainties inherent in cost of equity estimation and the importance of considering different alternative models.

Keywords: Cost of equity, bank profitability.

1 Introduction

The cost of equity (COE) is the return investors expect for holding the equity of a company. It is a key determinant of firms' funding costs. In the case of banks, COE impacts their ability to raise new capital, constraining their intermediation capacity and limiting credit provision to the real economy. From a regulatory point of view, COE is a key measure for assessing the cost to banks of an increase in capital requirements. Unlike the cost of debt, COE is an unobserved quantity that needs to be estimated. A range of different approaches to estimating COE has been proposed. These approaches can sometimes yield significantly different estimates, and there is no certainty as to which methodology is the most appropriate in any given case.

This paper aims to analyse various COE estimation methodologies and apply them to a sample of euro area banks. These methodologies can be broadly grouped into two categories: i) factor analysis of stock market returns, and ii) dividend discount models. The first category is based on arbitrage theory, and has recently been used by Adrian, Friedman, and Muir (2015), Altavilla et al. (2021), Kovner and Van Tasseel (2022) and Zsurkis (2022), among others. These methods are backward-looking, drawing on the co-movement of past firm returns with a series of common risk factors to produce COE estimates. The second category is based on discounting the future cash flows of a firm. It has recently been used in Mohanram and Gode (2013), Altavilla et al. (2021) and Dick-Nielsen, Gyntelberg and Thimsen (2022), among others. This approach is forward-looking and, in principle, is able to better account for current market expectations. However, it depends crucially on analysts' forecasts, which can entail sizeable errors.

In this paper, several of the most widely used models from each category are estimated. Within the first group (factor analysis of stock market returns), the two most popular factor models are considered – the capital asset pricing model (CAPM) and Fama and French (1993) (FF) –, analysing both the constant and the time-varying cost of risk. In terms of dividend discount models, the paper focuses on those based on Fuller-Hsia (1984) and Ohlson and Juettner-Nauroth (2005), and the free cash flow to equity model of Altavilla et al. (2021). A comparison is made between the results of these models and their combinations across European and Spanish banks over the last two decades, from 2000 Q4 to 2023 Q3. It is found that the different model estimates show similar time variation over the entire sample period, although the differences in levels can at times be substantial, underscoring the uncertainty inherent in COE estimates.

In addition, the relationship between the COE estimates and bank fundamentals is examined. The findings are broadly in line with previous findings on the association between bank characteristics and COE. For the best performing models, a higher CET1 ratio tends to be associated with lower COE, while the opposite holds for higher NPLs and interbank deposit ratios. The results, however, depend on the econometric specification and the choice of COE model. Overall, dividend discount models, particularly the free cash flow to equity model of Altavilla et al. (2021), yield COE estimates which show a somewhat stronger association with bank fundamentals. Meanwhile, groups of banks based on observable characteristics are also analysed. It is found that factor models tend to perform better for larger banks, while the performance of dividend discount models is less dependent on bank size. Specifically, factor models identify a much clearer negative (positive) impact of CET1 (NPL) ratios on COE for larger banks.

The rest of the paper is organized as follows. In Section 2 the various COE estimation approaches considered are described. Section 3 sets out the main empirical results and Section 4 details the conclusions drawn.

2 Methodology

2.1 Factor models: using historical market returns to estimate COE

The models in the first class are based on a multi-factor approach. The underlying idea is that the market returns of a firm can be broken down into a purely idiosyncratic component, and a component that depends on how exposed a firm is to a number of risk factors. Since investors can diversify away the idiosyncratic component of the return (by including many other firms in their portfolio), the only relevant component for pricing is the one dependent on exposure to common risk factors. Hence, in this setting, the COE is the weighted sum of the prices of the risks to which an asset is exposed, where the weights capture the sensitivity of that asset to each factor, usually quantified as a regression coefficient.

The simplest model in this class is the capital asset pricing model (CAPM) (Sharpe 1964, Lintner 1965), which can be shown to apply provided certain relatively restrictive conditions are met, and which features a single risk factor. The CAPM is famed for its simplicity and continues to be popular among academics and practitioners (see, for example, Kovner and Van Tasseel (2022) and references therein). However, it does yield some clear pricing anomalies.[1] The model of Fama and French (1993) adds two additional risk factors, resolving some of the issues with the CAPM.[2]

Within multi-factor models the COE is estimated in two steps. In the first step the returns of a firm (y_{it}) in excess of the risk-free rate (r_t) are regressed on a constant (α_i) plus the risk factors (X_t):

$$y_{it} - r_t = \alpha_i + \beta'_{i,t} \cdot X_t + \varepsilon_{it} \qquad [1]$$

Here the coefficients (β'_i) are the loadings that quantify the exposure of the returns of a firm to the risk factors. In the second step, the COE of a firm is calculated by simply multiplying the estimated loadings by the price of risk of each risk factor (λ):

$$COE_{i,t} = \hat{\beta}'_{i,t} \cdot \lambda_t + r_t \qquad [2]$$

Both the sensitivity of the returns of the firm (the estimated factor loadings $\hat{\beta}'_{i,t}$) and the price of risk (λ_t) may vary over time. In this paper, in order to estimate factor loadings that can vary over time, (1) is estimated using overlapping 1-year windows (based on weekly returns). This approach is simple and transparent and affords sufficient flexibility.[3] Since the factors used are market returns (see below) the price of risk can be computed as the expectation of the factors. To obtain prices of risk that can vary over time, weighted means with backward-looking exponentially decaying weights are calculated.

2.2 Dividend discount models: using forward-looking information to estimate COE

The models in the second class estimate a firm's COE using the relationship between its price and the expected dividends, as follows:

$$P_{i,t} = \sum_{k=1}^{\infty} \frac{E_t\left[D_{i,t+k}\right]}{\left(1+COE_{i,t}\right)^k} \qquad [3]$$

1 For example, firms with low market capitalization or high book-to-market value tend to have systematically higher returns than those predicted by the CAPM.

2 The Fama and French (1992) model explains a larger share of the cross-sectional variation in stock returns than the CAPM, at the cost of somewhat greater complexity and a lack of microfundations.

3 The overlapping window method to estimate time-varying betas has been used, for example, in Kovner and Van Tassel (2022). An alternative means of obtaining time-varying loadings, used recently in Altavilla et al. (2021), is to estimate (1) with the dynamic conditional beta approach of Engle (2016). This approach can in principle yield estimates that respond more rapidly to changes over time; in fact, Altavilla et al. (2021) argue that the dynamic conditional beta approach yields more timely estimates than using 2-year overlapping windows. However, a 1-year window is a good compromise between timeliness and efficiency, and the added complexity of the dynamic conditional beta approach arguably outweighs the potential gains in timeliness.

where $P_{i,t}$ is the price of firm i at time t, and $E_t\left[D_{i,t,t+k}\right]$ is the expectation at time t of the dividends at time $t+k$. In other words, the COE is the discount rate that investors apply to the expected dividends in order to value the firm. Since the long-term expectations of dividends are extremely uncertain, different models approximate them in different ways.

An early example of a model in this class that yields a particularly simple COE formula is that of Fuller and Hsia (1984). In their work, it is assumed that the growth rate of the dividends takes an initial value g_0 and evolves linearly to a value of g_L after H periods. This approach, applied to the general European stock market and combined with a CAPM to obtain COE values for the banking sectors of different countries, has been used in European Central Bank (2016) and Fernández Lafuerza and Mencía (2021).

A more recent related model was proposed by Ohlson and Juettner-Nauroth (2005). It also starts with (3), but assumes that the extraordinary growth in expected earnings above a benchmark, based on current earnings discounting dividends, itself grows at a constant rate g_L. A simplified version of this model is obtained assuming $g_L=0$ and ignoring dividends, as in Easton (2004).

More recently, Altavilla et al. (2021) employed another method of this type, which they refer to as the free cash flow to equity method (FCFE). Here, rather than discounting expected dividends, as in (3), the whole free cash flow (unretained earnings after tax) is discounted. Further details on the four dividend discount models used can be found in Annex 1.

3 Empirical analysis

This section describes the empirical implementation of the models detailed above. The resulting COE estimates are compared and analysed in terms of their relationship with bank fundamentals.

3.1 Data

The COE of euro area banks is estimated using several datasets. For the factor models, data on equity returns, market capitalization and risk-free rates are obtained from Refinitiv.[4] The factors used in the factor models come from the Kenneth R. French online database.[5] For the dividend discount models, use is made of analyst consensus forecasts of dividends and earnings per share up to 4-years ahead, as well as realised dividends, earnings per share and share price, for individual banks from the Institutional Brokers' Estimate System (I/B/E/S)

4 The Euro-Mark weekly deposit rate is used as a risk-free proxy.

5 See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. In the cases of the HML and SMB factors, data in euros is not obtained immediately. To this end, the 6 size and book-to-market sorted portfolios (available in the Fama-French database) are used as the starting point, before converting them at daily frequency into euros. Weekly returns of these 6 portfolios are subsequently calculated. Finally, the formulas available on the Kenneth R. French online database are used to compute the HML and SMB factors in euros.

database (Refinitiv Eikon). Long-term expected nominal GDP growth data from Consensus Economics are used to proxy the long-term earnings growth (g_L). Thus, an unbalanced panel dataset is assembled containing 89 listed banks from 15 euro area countries (see Annex 2). The sample of banks differs slightly across COE models due to data availability. The COE is estimated weekly in the case of factor models and monthly in the case of dividend discount models, and the mean value for the quarter is taken. The sample period runs from 2000 Q4 to 2023 Q3. For the analysis of bank fundamentals (described in Section 3.5) the COE data is combined with quarterly balance sheet data obtained from S&P Global Market Intelligence.

3.2 Factor models

In the factor approach, the two most frequently used models are considered: CAPM and Fama and French (1993) (hereinafter FF). The main difference between the two is the number of factors included in the analysis. The following three factors are considered:

1. The excess return of an overall European stock market index.[6]

2. The high-minus-low factor (HML). This factor quantifies the additional return for firms with high book-to-market value. It is calculated as the spread between firms with high and low book-to-market value ratios (below the 30th and above the 70th percentile).

3. The small-minus-big factor (SMB). This factor can be interpreted as a size factor, as it captures the stock return spread between small and large firms (below the 10th and above the 90th percentile), with size measured by market capitalisation.

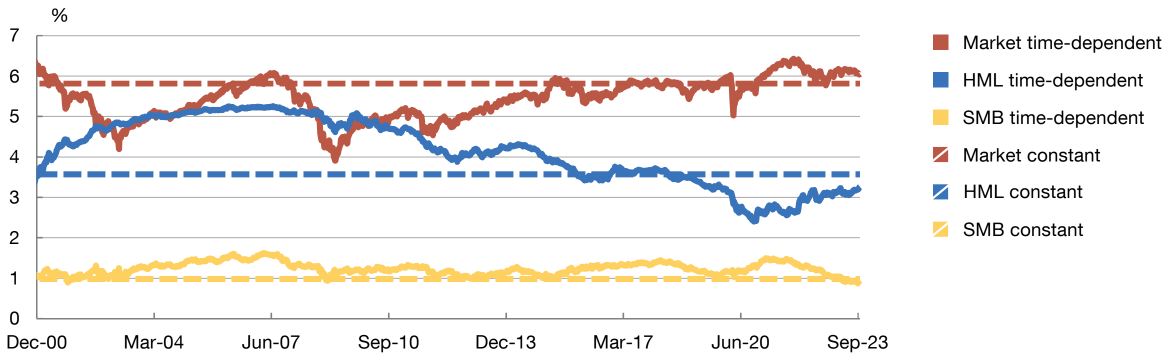
The CAPM includes the first factor only, while the FF model includes all three factors simultaneously. Since all the factors are portfolio returns, the price of risk corresponding to each factor is simply the expected value of the factor. In order to allow for the possibility that the price of risk might change over time, a time-dependent variation of each model is considered where the price of risk is computed as a weighted mean of past values of the factor, with an exponentially decaying weight.[7]

Chart 1 shows the estimated time-varying prices of risk in comparison to their constant counterparts. Notably, the price of risk of the market factor increased steadily in the run-up to the 2008 financial crisis, before falling sharply and then returning to historical values around 2015. The price of risk of the HML factor was above trend between 2001 and 2015, and then

6 For consistency, the market index from Fama French is considered. Given that it is expressed in dollars, this index must be converted back into euros, transforming the frequency from daily to weekly. In any event, it is very similar to the Stoxx 600 Europe Index, as the correlation between the weekly returns of these two indices is about 98%.

7 The formula is $\lambda_t = (1-\gamma)^t \lambda_0 + \gamma \sum_{i=1}^{t} f_i (1-\gamma)^{t-i}$, taking λ_0 equal to the unweighted mean in the complete sample. The decay parameter γ is set to 0.00044186, so that the weight decays to 0.1 after 100 years. A low value is chosen for the decay parameter to avoid prices of risk that change sign over time and to consider a small variation around the constant price of risk baseline.

Chart 1
Cost of risk associated with the different factors



SOURCE: Devised by authors using data from the Kenneth R. French online database.

declined steadily until very recently, suggesting a market preference for growth stocks in the last few years. The SMB factor, meanwhile, shows very minor variations in comparison to its time-invariant version, suggesting that the size premium changed little over time.

When computing the loadings in equation (1), weekly returns exactly equal to zero are dropped, as they are mostly due to public holidays or database updating delays. Returns at percentiles 0.1 and 99.9 are further winsorized to limit the influence of outliers that can be attributed to limited liquidity in some stocks and periods.

3.3 Dividend discount models

Dividend discount models depend crucially on the short and long-term growth of expected earnings. The short-term growth rate in earnings, g_s^{earn} (see Annex 1), is calculated as the geometric average of 4-year ahead growth (based on analysts' expectations) in earnings per share.[8]

In the Fuller Hsia (1984) model, g_0 corresponds in principle to the expected short-term growth rate in dividends. Although such data are available in the I/B/E/S database, they are found to be somewhat volatile and are often missing, so the expected growth rate of earnings, g_s^{earn}, is used instead. The time the growth rate of dividends takes to change from g_0 to g_L is set to 5 years. The estimated short-term growth rate of earnings, g_s^{earn}, can sometimes be highly volatile, leading to implausible COE values. To avoid this problem, g_s^{earn} is winsorized at 0 and 100% (yearly growth rate). Further, the time series of g_s^{earn} for each bank is smoothed with an exponential filter.[9]

8 $g_s = \sqrt[3]{E\left[Earn_{t+4}\right] / E\left[Earn_{t+1}\right]}$. If four-years ahead expectations are not available, the corresponding formula with three (if available) or two-years ahead is used. If no expectation data are available, the realized growth with respect to twelve months prior is used.

9 The formula is the same as that shown in footnote 5. The value of the decay parameter used is 0.1746, so that the weight decreases to 0.1 after 12 months.

In the Free Cash Flow to Equity (FCFE) model of Altavilla et al. (2021) a value of retained earnings equal to 10% is assumed (a somewhat small value). Indeed, for the sample of banks for which data are available, the median of this value between 2006 and 2023 is close to 70%. Given that this period was characterized by significant increases in capital requirements, the projected value going forward is likely to be lower. An intermediate choice is therefore made to set it at 40%.

For the long-term growth rate, g_L, the expected nominal long-term (from six to ten-years ahead) GDP growth of the euro area (obtained from Consensus Economics) is used.

3.4 Aggregate results

Chart 2 reports aggregate time series at the euro area level of the estimated results of eight COE models: four factor models and four dividend discount models. The factor models are the CAPM and FF specifications with constant and time-varying prices of risk. The dividend discount models are based on Fuller Hsia (1984), Ohlson and Juettner-Nauroth (2005), a simplified version of the latter based on Easton (2004), and a free cash flow to equity model (FCFE) used in Altavilla et al. (2021).

Across the four factor models the trend is broadly similar, with marked increases associated with the GFC, the European sovereign crisis and the monetary policy tightening from mid-2022 onwards. However, the FF models pick up more variation in COE in the first half of the sample, and somewhat less in the second half, suggesting significant time variation in the loadings of factors other than the market factor.[10] The magnitude of FF models also appears larger than that of CAMP models, due to these banks having a positive average exposure to the HML factor (i.e. they behave as value stocks).[11] The time-varying specifications yield results very close to those with a fixed price of risk, with some differences in crises such as the GFC and the European sovereign debt crisis.

The estimates from the dividend discount models show similar time-series variation relative to the factor models, but they reveal a more abrupt rise and fall around the 2008 crisis, and a somewhat more stable pattern thereafter. The Fuller Hsia (1984) model tends to deliver lower estimates. Overall, it is found that the aggregate results from the different models have similar time-series variation, but their levels can differ substantially, by over 5 percentage points.

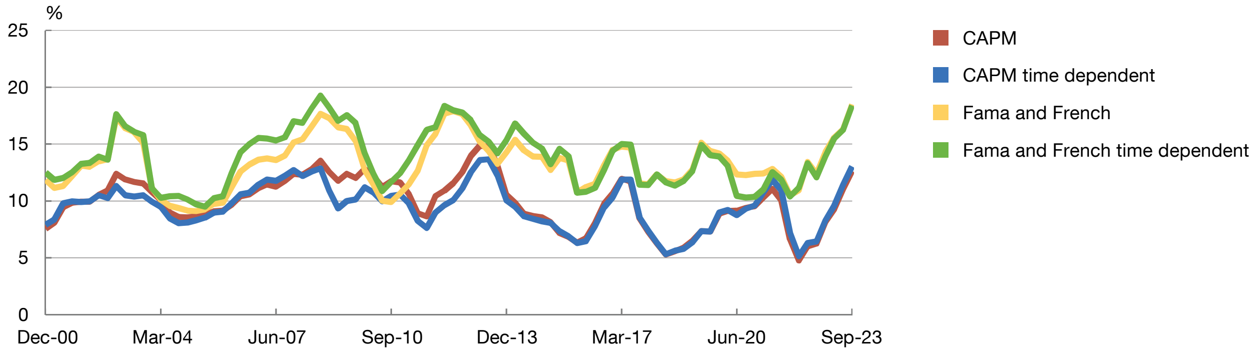
In order to obtain a single COE measure, the average across the eight models considered is computed. Mohanram and Gode (2013) show that taking the simple mean of COE across

10 Since the market factor is present in both the CAPM and the FF model, the differences over time in the variability of FF versus CAPM estimates, observed both with constant and time-varying costs of risk, can be attributed to changes over time of the other loadings. In fact, the within-bank standard deviation (across time) of the loadings of the HML and SMB factors have a mean of 1.0 (median 0.9), while that of the market factor is 0.5 (median 0.5).

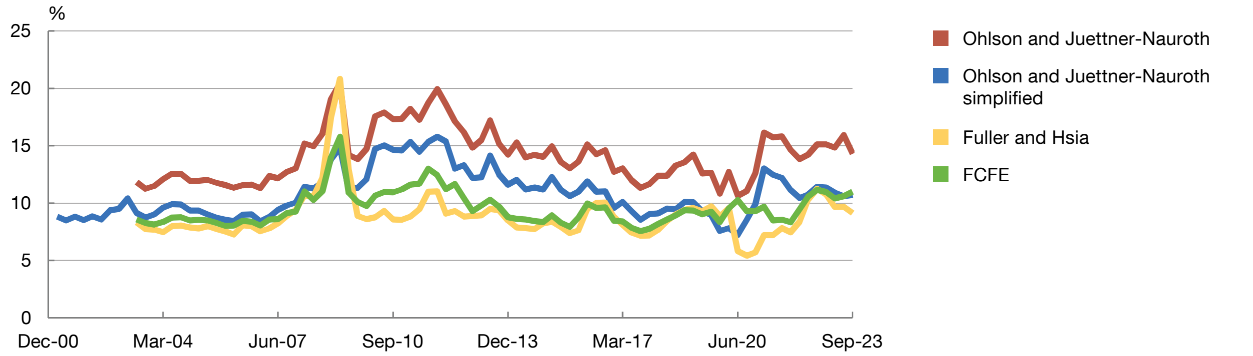
11 The median of the loadings over the HML factor is 0.8, and the mean is 1.1; for the SMB factor, which has a smaller price of risk (see Chart 1), the median is 0.3 and the mean 0.4.

Chart 2
Distribution of factor and dividend discount models

2.a Factor models of COE across the EU



2.b Dividend discount models of COE across the EU

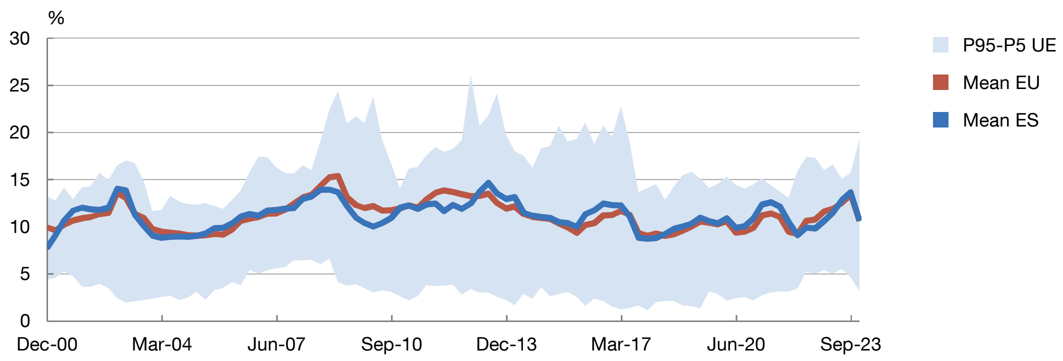


SOURCE: Consensus Economics, Datastream, Refinitiv Eikon.

several model estimates yields a more accurate estimate with lower measurement error. The averaging approach is also taken in Dick-Nielsen, Gyntelberg and Thimsen (2022) and Altavilla et al. (2021). Chart 3 displays the time evolution of this measure for the euro area and Spanish banks, as well as a confidence interval based on the variation across banks.

The first observation is that the average COE estimate is smoother than the individual COE estimates. Secondly, there is significant dispersion across banks in each period and limited differences between the results for Spain and the EU as a whole. During the observation period, the aggregate COE of Spanish banks was remarkably close to that of the average for the euro area. It was somewhat below the mean during the GFC, but rose slightly higher during the sovereign debt crisis. Notably, with the onset of the COVID-19 pandemic, the COE of Spanish banks increased more than for their peers in the euro area. However, this trend reversed with the start of the 2022 monetary policy tightening. Most recently, the COE of the euro area started rising again, while that of Spanish banks did so at a slightly faster pace.

Chart 3
Distribution of COE models



SOURCE: Consensus Economics, Datastream, Refinitiv Eikon.

3.5 Determinants of COE

Previous research has suggested that several bank characteristics (in particular, bank solvency, soundness of asset portfolio, bank size and profitability) are correlated with COE. For instance, better capitalised banks may benefit from a lower COE (Dick-Nielsen, Gyntelberg and Thimsen, 2022, ECB, 2011), while banks with higher credit risk may be faced with a higher COE, related to a perception of worse asset quality. The relationship between COE and bank size is less clear due to counterbalancing factors associated with the latter, such as implicit state guarantees and complexity.

Chart 4 plots the distribution of the average COE for different subsamples of banks, split by the median of balance sheet characteristics.[12] Panel 4.1 shows that banks with above-median CET1 ratios and profitability tend to have lower COE, which is in line with the results from the literature. It is notable that the positive trend in profitability over the most recent years (blue line) has not been reflected in lower COE estimates, as was the case in previous cycles. One possible explanation may lie in investors' uncertainty over the temporal effect of this recent improvement in ROE and the associated risks. In terms of asset quality, as expected, banks with higher than median NPL ratios have a higher COE, although the difference is narrower than in the case of CET1 and profitability. In the case of size of bank assets, the difference between the COE of banks of above-median and below-median asset size is more volatile, with larger banks generally tending to have a higher COE, bearing out the complexity argument.[13] These associations are analysed in more details with a panel regression below.

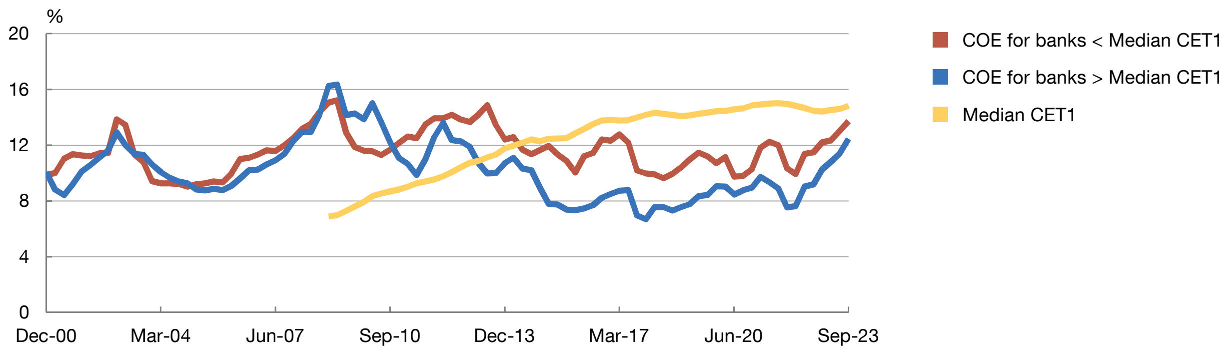
12 For each bank the across-time mean value of each balance sheet item is calculated, followed by the computation of the between-bank median value of balance sheet items and the split of the sample of banks by these values. The data are available from 2008 Q1.

13 Note that the differences are clearer in the latter part of the sample, where information about the balance sheet items is available. This may be due to the fact that the split is based on information for that sub-sample only.

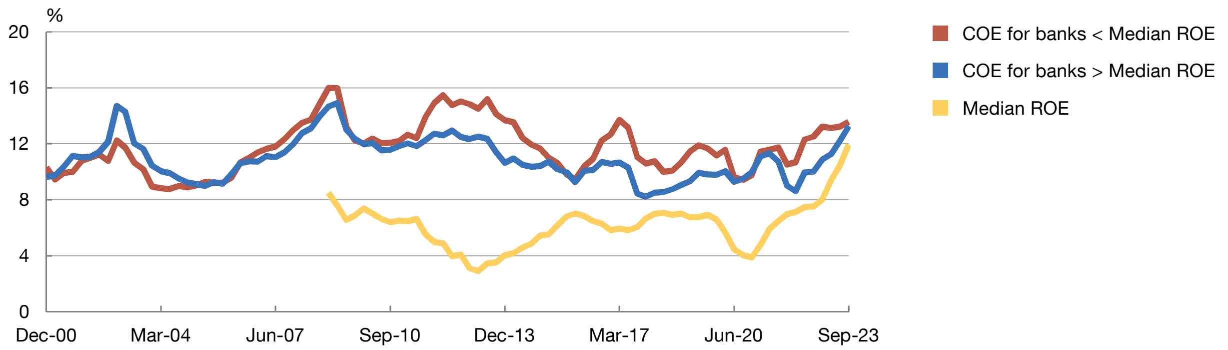
Chart 4

Average COE and bank characteristics - CET1 and RoE

4.a COE by median CET1



4.b COE by median RoE



SOURCES: Consensus Economics, Datastream, Refinitiv Eikon, SNL Financial.

Two linear fixed-effects (FE) econometric specifications are estimated. The first includes interactions of country and time dummies (year-quarter) in order to capture country-specific characteristics that vary across time, such as overall economic activity or sovereign premia. The second specification accounts for bank FE as well as an overall time trend.[14] In both specifications standard errors are robust to serial correlation (clustered at bank level) and heteroscedasticity.

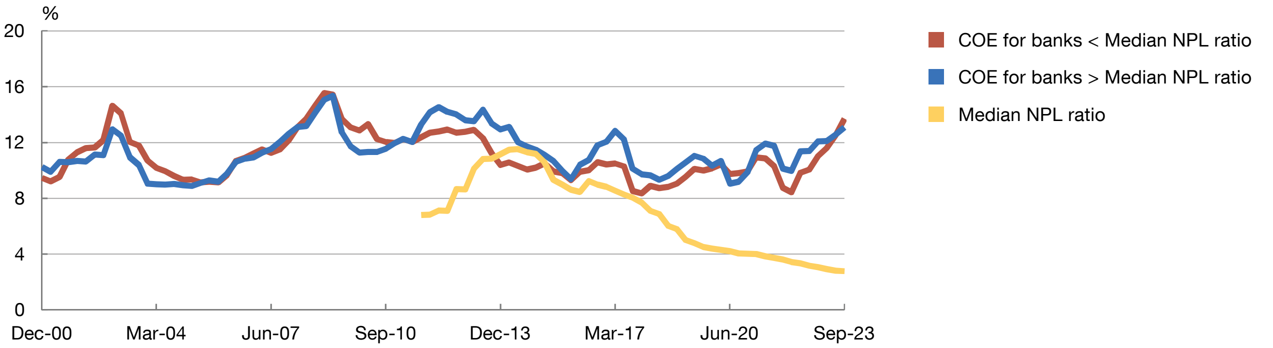
The COE estimates are combined with quarterly bank-level data on the following balance-sheet items. First, each bank's solvency is proxied using the ratio of its core capital, common equity tier 1 (CET1), to its risk-weighted assets. The expectation is that higher capitalization should be associated with lower COE. Second, credit risk is proxied using the non-performing (NPL) loans-to-total loans ratio. It is expected that banks with higher NPL ratios will have a higher COE, given the worse quality of their assets. Third, banks' funding structures are captured by interbank deposits over total assets. Compared to retail deposits and other more stable sources of funding, banks that rely more on interbank deposits are expected to have a

14 Additionally, models with country-time fixed effects interactions and bank fixed effects (FE) have been estimated. However, the statistical power is very limited due to the modest bank-time variation in the data.

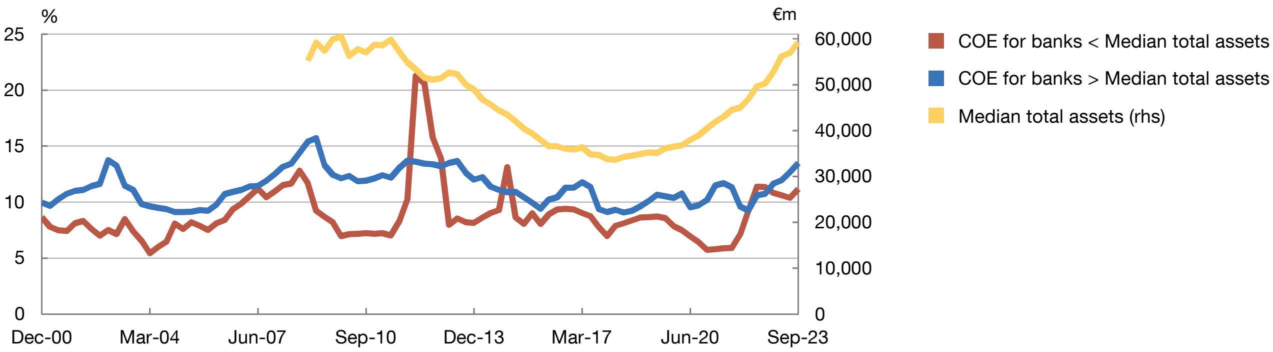
Chart 5

Average COE and bank characteristics - NPL ratio and total assets

5.a COE by median NPL ratio



5.b COE by median bank size



SOURCES: Consensus Economics, Datastream, Refinitiv Eikon, SNL Financial.

higher COE. Lastly, the cost-to-income ratio is used as a proxy of operational efficiency. Higher operating expenses as a proportion of income should be reflected by a higher COE.[15] As a control, the log of assets is included as a measure of bank size. Observations with negative estimated COE are dropped, as such implausible values are likely due to measurement error or high-stress events, where no equity investment in a bank can be expected.[16]

Tables 1 and 2 show the results for the factor and dividend discount models, respectively. The estimated signs on bank fundamentals are generally in line with the theoretical predictions described above. However, the size of the estimates largely depends on the COE model selection and empirical specification, and statistical significance is generally weak.

The signs of the coefficients for CET1 are negative, as expected, suggesting that higher capitalization reduces the COE of new emissions. In particular, a 1 pp increase in the CET1 ratio

15 As robustness checks, the leverage ratio and ROA have also been used, as substitutes of the CET1 and cost-to-income ratios, respectively. The results from all specifications are consistent and are available upon request.

16 The observations with negative values in terms of the CET1 ratio and cost-to-income were also dropped.

Table 1
Factor models

Variables	CAPM				Fama French (1993)			
			Time-dependent				Time-dependent	
	[1]	[2]	[1]	[2]	[1]	[2]	[1]	[2]
CET1 ratio	-0.155	-0.035	-0.153	-0.037	-0.217	-0.058	-0.223	-0.037
	(0.095)	(0.054)	(0.094)	(0.053)	(0.148)	(0.086)	(0.149)	(0.088)
NPL ratio	0.021	0.079*	0.020	0.075*	0.070	0.113**	0.078	0.116**
	(0.091)	(0.042)	(0.089)	(0.040)	(0.136)	(0.056)	(0.142)	(0.055)
Interbank deposit rati	0.010	0.002	0.008	0.001	0.019	0.125	0.018	0.109
	(0.042)	(0.034)	(0.041)	(0.032)	(0.067)	(0.089)	(0.066)	(0.086)
Cost-to-income ratio	-0.003	-0.006	-0.003	-0.006	0.004	-0.023*	0.004	-0.022*
	(0.010)	(0.007)	(0.010)	(0.007)	(0.013)	(0.012)	(0.013)	(0.011)
Log (assets)	0.758***	1.615**	0.757***	1.456**	1.331***	2.027**	1.251***	2.453**
	(0.141)	(0.683)	(0.140)	(0.648)	(0.194)	(0.961)	(0.194)	(1.031)
N bank-obs	880	1,047	880	1,047	881	1,047	881	1,047
N banks	57	59	57	59	58	59	58	59
Adjusted R2	0.538	0.596	0.527	0.589	0.589	0.605	0.589	0.609
Time FE		Yes		Yes		Yes		Yes
Time-Country FE	Yes		Yes		Yes		Yes	
Bank FE		Yes		Yes		Yes		Yes

SOURCE: S&P Global Market Intelligence and devised by authors.
Note: Specification [1] includes country-time fixed effects. Specification [2] includes bank and time fixed effects. Robust standard errors, clustered by bank, in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

is associated with a 0.2-0.3 pp decrease in COE. However, this effect is statistically significant in only two specifications for the dividend discount models. Conversely, the coefficients for NPL ratios are positive, confirming that higher realized credit risk is likely to increase the COE. Moreover, this finding is statistically significant in the bank and time FE specification of factor models and the country-time FE specifications of several dividend discount models.

A positive and significant effect of interbank deposits is obtained in most specifications, particularly in dividend discount models, and is also in line with the theoretical predictions. This suggests that relying more heavily on interbank financing increases COE. Conversely, the estimates of the cost-to-income ratio are not statistically significant in most specifications.

Comparing performance across COE models, the results indicate that dividend discount models tend to show a somewhat stronger relationship with bank fundamentals.[17] Among these, the free cash flow to equity (FCFE) model of Altavilla et al. (2021) displays the best performance, while the one based on Fuller and Hsia (1984) performs worst. This finding may be due to the fact that the Fuller and Hsia (1984) model explicitly relies on dividends as the only form of shareholder compensation, while the FCFE model includes all after-tax un-retained

17 To ensure comparability across models, robustness checks have been performed with the same sample across models. The results are qualitatively very similar and are available upon request.

Table 2
Dividend discount models

Variables	Ohlson and Juettner-Nauroth (2005)		Simplified		Fuller Hsia (1984)		FCFE	
	[1]	[2]	[1]	[2]	[1]	[2]	[1]	[2]
CET1 ratio	-0.242	-0.104	-0.119	-0.223	-0.201**	-0.052	-0.302*	0.202*
	(0.157)	(0.182)	(0.160)	(0.189)	(0.085)	(0.075)	(0.153)	(0.102)
NPL ratio	0.165**	-0.030	0.253***	-0.011	-0.084*	-0.006	0.120**	0.020
	(0.072)	(0.055)	(0.068)	(0.054)	(0.048)	(0.023)	(0.046)	(0.021)
Interbank deposit ratic	0.159**	0.402***	0.226***	0.378***	-0.017	0.066**	0.203***	0.150***
	(0.064)	(0.116)	(0.081)	(0.121)	(0.030)	(0.030)	(0.033)	(0.044)
Cost-to-income ratio	0.069	0.043	0.032	0.040	-0.006	0.005	0.054*	-0.022
	(0.051)	(0.080)	(0.048)	(0.073)	(0.012)	(0.010)	(0.029)	(0.015)
Log (assets)	-0.454	3.727	-0.271	3.672	-0.326	-0.256	-1.041***	-0.671
	(0.316)	(3.269)	(0.308)	(3.677)	(0.213)	(1.320)	(0.296)	(1.427)
N bank-obs	655	832	670	847	914	1079	795	975
N banks	38	44	39	45	50	56	49	54
Adjusted R2	0.381	0.411	0.409	0.469	0.289	0.401	0.384	0.672
Time FE		Yes		Yes		Yes		Yes
Time-Country FE	Yes		Yes		Yes		Yes	
Bank FE		Yes		Yes		Yes		Yes

SOURCE: S&P Global Market Intelligence and devised by authors.
Note: Specification [1] includes country-time fixed effects. Specification [2] includes bank and time fixed effects. Robust standard errors, clustered by bank, in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

profits. The use of share repurchases as pay-out methods may make COE estimates that rely solely on dividends less accurate. Specifications including bank fixed effects show a somewhat less clear association between COE estimates and bank fundamentals. This indicates that time invariant differences between banks are quite relevant when it comes to explaining COE. It might also be due to limited time variation in balance-sheet variables in the sample.[18]

The estimates of bank size are positive and highly significant in factor models, while negative and only occasionally significant in the dividend discount models. These findings are in line with Altavilla et al. (2021) and Kovner and Van Tassel (2022). As discussed above, there are two hypotheses regarding the association between bank size and COE. On the one hand, the too-big-to-fail literature (e.g. Goel et al (2019), Kelly et al. (2016) and Gandhi and Lustig (2015), among others) suggests that larger banks may get a discount on their COE thanks to implicit state guarantees. On the other hand, bank size also reflects complexity. For instance, previous research shows that larger institutions tend to display lower overall efficiency scores (Huljak et al, 2019). In addition, Demsetz and Strahan (1997) argue that while large banks may perform better than smaller banks in terms of risk diversification, this may be not enough to compensate

18 Note that balance sheet data are only available from 2010 and are often missing for many banks (on average, a bank has complete data for 19.4 quarters).

Table 3
Results for mean COE across models

Variables	All models		Factor models		Dividend discount models	
	[1]	[2]	[1]	[2]	[1]	[2]
CET1 ratio	-0.226**	-0.055	-0.185	-0.043	-0.233*	-0.044
	(0.096)	(0.050)	(0.120)	(0.064)	(0.118)	(0.071)
NPL ratio	0.143***	0.053**	0.048	0.096**	0.139***	-0.015
	(0.053)	(0.026)	(0.114)	(0.047)	(0.048)	(0.036)
Interbank deposit ratio	0.042	0.124***	0.016	0.060	0.094**	0.191***
	(0.050)	(0.032)	(0.054)	(0.056)	(0.045)	(0.044)
Cost-to-income ratio	-0.002	-0.011	0.001	-0.014	-0.003	0.002
	(0.016)	(0.010)	(0.011)	(0.009)	(0.033)	(0.021)
Log (assets)	0.370*	1.863***	1.032***	1.874**	-0.301	0.449
	(0.189)	(0.647)	(0.162)	(0.765)	(0.283)	(1.582)
N bank-obs	1,143	1,298	884	1,049	915	1,080
N banks	68	71	58	59	50	56
Adjusted R2	0.308	0.475	0.560	0.619	0.175	0.359
Time FE		Yes		Yes		Yes
Time-Country FE	Yes		Yes		Yes	
Bank FE		Yes		Yes		Yes

SOURCE: S&P Global Market Intelligence and devised by authors.
Note: Specification [1] includes country-time fixed effects. Specification [2] includes bank and time fixed effects. Robust standard errors, clustered by bank, in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

for the higher risk associated with greater leverage or riskier lending.[19] As a result, the relationship between bank size and COE is less clear (Kovner and Van Tassel, 2022). Bank size may also affect the association between COE and bank fundamentals. This issue is explored by interacting every bank observable with a dummy based on bank assets.[20] The findings indicate that the negative association between COE and higher capitalisation holds predominantly for larger banks (see Annex 3). The same can be said of the NPL ratio in the case of factor models.[21] These results indicate that factor-based COE estimates tend to be more strongly related to bank fundamentals for larger banks. This may be due to the fact that larger banks' stock returns (due to their higher liquidity, inclusion in indexes and greater scrutiny by analysts) are closer to the no-arbitrage ideal implicit in factor models. It is also possible that the common factors considered are less relevant for smaller banks, which are more affected by local developments.

Finally, Table 3 displays the association of bank fundamentals with a COE averaged across models. The aggregate approach also offers evidence of some association between COE and

19 Bank size can increase risk-taking incentives due to implicit too-big-to-fail subsidies, or by reducing charter value, see De Niccolo (2000).

20 Every bank fundamental is interacted with a dummy that takes a value of one if the average assets of the bank are equal to or larger than the median, and zero otherwise. For details, see the Annex 3.

21 The relationship with the interbank deposits ratio only holds for smaller banks in the case of factor models and generally applies irrespective of size in the case of dividend discount models.

bank characteristics. In particular, the coefficients of the capital ratio, NPLs and the interbank deposit ratio are statistically significant, especially in the aggregate for the dividend discount models (country-time FE specification). Overall, bank fundamentals explain around one-third of the variation in COE estimates.[22]

4 Conclusions

Several methods for estimating the COE of euro area banks have been analysed in this article. At the aggregate level it is found that, while they tend to yield similar results in terms of time evolutions, such methods can lead to significant differences in levels, often in the order of five percentage points. At the individual level, COE estimates from dividend discount models tend to show a relationship with fundamentals (solvency, credit risk, funding profile) more in line with expectations than those based on factor models. Factor model estimates show a clearer relationship with bank observables for larger banks. Overall, the findings of this study underscore the uncertainties inherent in COE estimation and the importance of considering several alternative methodologies.

22 Using a Shapley value decomposition of the coefficient of determination, the CET1 ratio accounts for 11.5%, the NLP ratio for 11.2%, the interbank deposit ratio for 5.7%, the cost-to-income ratio for 0.3%, and bank size for 6.2% of this explained variation.

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Annex 1 Dividend discount models

As detailed in the main text, dividend discount models start from the following basic formula:

$$P_{i,t} = \sum_{k=1}^{\infty} \frac{E_t\left[D_{i,t+k}\right]}{\left(1+COE_{i,t}\right)^k} \quad [A.1]$$

The different models differ in how expected future dividends are approximated. In the Fuller and Hsia (1984) model it is assumed that expected dividends initially grow at a rate g_0, which decreases linearly to a value of g_L after H periods. Under those assumptions, Fuller and Hsia (1984) derive an approximated formula for COE in (3), as follows:

$$COE_{i,t}^{FH} = \frac{D_{i,t}}{P_{i,t}}\left[1+g_0+H\left(g_L-g_0\right)\right]+g_L \quad [A.2]$$

The Ohlson and Juettner-Nauroth model (2005) also starts with (A.1), but adds the following assumption:

$$\frac{E_t\left[EPS_{t+k+2}\right]-E_t\left[EPS_{t+k+1}\right]-COE_t\left\{E_t\left[EPS_{t+k+1}\right]-E_t\left[D_{t+k+1}\right]\right\}}{E_t\left[EPS_{t+k+1}\right]-E_t\left[EPS_{t+k}\right]-COE_t\left\{E_t\left[EPS_{t+k}\right]-E_t\left[D_{t+k}\right]\right\}} = \gamma, \forall k \geq 1$$

In the expression above, $ROE_t\left\{E_t\left[EPS_{t+k}\right]-E_t\left[D_{t+k}\right]\right\}$ is the expected (at time t) return between t+k and t+k+1 of the earnings retained at t+k, which can be seen as a benchmark growth rate. $E_t\left[EPS_{t+k+1}\right]-E_t\left[EPS_{t+k}\right]$ is the expected growth or earnings over that same period. Thus, the model assumes that the expected earnings above the benchmark itself grow at a rate $\gamma-1$. Moreover, assuming that $\frac{E_t\left[D_{t+k}\right]}{E_t\left[EPS_{t+k}\right]}=C$ for k≥T, with T being some future date, and $C \geq \left(1+COE_t-\gamma\right)/COE_t$, it can be shown that

$$\gamma = \lim_{k\to\infty} \frac{E_t\left[EPS_{t+k+1}\right]}{E_t\left[EPS_{t+k}\right]} \equiv 1+g_L$$

Based on these assumptions, together with (A.1), it can be shown that the COE takes the following expression:

$$COE_{i,t}^{OJ} = A_{i,t} + \sqrt{A_{i,t}^2 + \frac{E_t\left[EPS_{t+1}\right]}{P_{i,t}}\left(g_s^{earn}-g_L\right)}, \qquad A_{i,t} \equiv \frac{\left(g_L + \frac{E_t\left[D_{i,t+1}\right]}{P_{i,t}}\right)}{2} \quad [A.3]$$

With $g_s^{earn} \equiv \frac{E_t\left[EPS_{t+2}\right]-E_t\left[EPS_{t+1}\right]}{E_t\left[EPS_t+1\right]}$ being the short rate growth rate of the earnings per share. Further, assuming g_L = 0 and ignoring dividends, as in Easton (2004), a simplified version of the Ohlson and Juettner-Nauroth (2005) formula is obtained:

$$COE_t^{OJS} = \sqrt{\frac{E_t\left[EPS_{t+1}\right]}{P_{i,t}} g_s^{earn}} \quad [A.4]$$

More recently, Altavilla et al. (2021) propose another method of this type, which they refer to as the free cash flow to equity method (FCFE). Their starting point is a variation of (3):

$$P_{i,t} = \sum_{h=1}^{\infty} \frac{E_t\left[FCFE_{t+h}\right]}{\left(1+COE_t^{FCFE}\right)^h} \quad [A.5]$$

Where $FCFE_{t+h}$ is the free cash flow to equity at time $t+h$, which is further modeled as:

$$FCFE_{t+h} = \begin{cases} (1-RE)(1-\tau)EPS_{t+h}, \text{ if } EPS_{t+h} \geq 0 \\ EPS_{t+h}, \text{ if } EPS_{t+h} < 0 \end{cases} \quad [A.5]$$

with RE being the fraction of profits retained, τ the tax on profits and EPS_t the earnings per share at time t. They further assume that for h>7 years, $E_t\left[FCFE_{t+h}\right]$ grows at a constant rate g_L. Based on these assumptions and given values for $P_{i,t}$ and earnings expectations, (A.5) is an equation on COE_t^{FCFE}. Adding up the terms from h=7, the following is obtained:

$$P_t = \sum_{h=1}^{6} \frac{E_t\left[FCFE_{t+h}\right]}{\left(1+COE_t\right)^h} + \frac{E_t\left[FCFE_{t+7}\right]}{\left(COE_t - g_L\right)\left(1+COE_t\right)^6} \quad [A.6]$$

For $h=1,...,4$, for which earnings expectations are available from the I/B/E/S database, equation (A.5) is used to evaluate $E_t[FCFE_{t+h}]$. The marginal tax rate, τ, and the retained earnings share, RE, are fixed at 26.84% and 40%.[1] For $h=5,6,7$, it is assumed that $E_t[FCFE_{t+h}]$ grows a rate that exponentially approaches g_L that is $E_t\left[FCFE_{t+4+j}\right] = E_t\left[FCFE_{t+4+j-1}\right]\left(1+a^j g_s\right)$, with $a = \sqrt[3]{\frac{g_L}{g_s}}$, and $j=1,2,3$. As noted above, beyond $h=7$, $E_t[FCFE_{t+h}]$ is assumed to grow at a constant rate g_L. $E_t[FCFE_{t+h}]$ is also assumed to grow at the rate g_s for $h<5$ when expectations are not available. If one-year-ahead expectations are not available, the realized growth from 12 months prior is used.

Multiplying both sides of (A.6) by $\left(COE_t - g_L\right)\left(1+COE_t\right)$^6, a polynomial equation of 7th order in $1+COE_t$ is obtained. The equation simplifies to one of 6th order, once

1 Altavilla et al. (2021) use a value of 10% for retained earnings. Empirically, the median of this value in the 2006-2023 period is found to be 67%. Given that this period was characterised by important capital requirement increases, the appropriate value to project forward is likely smaller, but 10% is found to be rather small. An intermediate value of 40% is therefore chosen.

$E_t\left[FCFE_{t+7}\right]=(1+g_L)E_t\left[FCFE_{t+6}\right]$ is used. The equation is solved numerically with a Newton-Rapson method, starting with a value of 10%.

Note that the Fuller-Hsia formula (A.2) depends crucially on the current dividend yield. It does not appear in the simplified Ohlson and Juettner-Nauroth formula (A.4) or the FCFE formula (A.5), while it appears as expectation, together with earnings expectations, in formula (A.3). Thus, the Fuller-Hsia formula is more sensitive to dividend pay-out policy, and will tend to produce lower COE estimations if, for example, dividends are reduced in favour of share buybacks. The current trend towards more share buybacks at euro area banks (Couaillier, Dimou and Parle, 2023) could therefore make the Fuller Hsia model less appropriate.

Annex 2 Sample of euro area banks

Table A.2.1
Sample of euro area banks

Austria	Addiko Bank; Bank für Tirol und Vorarlberg; BAWAG Group; BKS Bank; Erste Group Bank; Oberbank; Raiffeisen Bank International; Volksbank Vorarlberg.
Belgium	Dexia; KBC Group.
Cyprus	Bank Cyprus Holdings Public; Hellenic Bank Public.
Estonia	AS LHV Group, Coop Pank AS
Finland	Aktia Pankki Oyj; Ålandsbanken; Alisa Pankki Oyj; Evli Pankki Oyj; Nordea Bank Abp; Oma Säästöpankki Oyj.
France	BNP Paribas; CRCAM de Toulouse 31; CRCAM Paris et IDF; CRCAM d'Ille-et-Villaine; CRCAM du Morbihan; CRCAM de Nord de France; CRCAM Brie Picardie; CRCAM du Languedoc; CRCAM Atlantique Vendee; Crédit Agricole; Natixis; Société Générale.
Germany	Aareal Bank; Comdirect bank; Commerzbank; Deutsche Bank; Deutsche Pfandbriefbk; Merkur PrivatBank; ProCredit Holding; Varengold Bank AG; UmweltBank AG
Greece	Alpha Bank; Attica Bank; Eurobank Ergasias; National Bank Greece; Piraeus Financial Holdings.
Ireland	AIB Group Plc; Bank of Ireland Group Plc; Permanent TSB Grp Hldgs plc.
Italy	Banca Carige; Banca Finnat Euramerica; Banca Generali; Banca IFIS; Banca Monte dei Paschi di Siena; Banca Popolare di Milano; Banca Popolare di Sondrio; Banca Profilo; Banca Sistema; Banco BPM Società per Azioni; Banco di Desio e della Brianza; Banco di Sardegna; BPER Banca; Credito Emiliano; FinecoBank; illimity Bank; Intesa Sanpaolo; Mediobanca Banca di Credito Finanziario; Poste Italiane; UniCredit ; Unione di Banche Italiane.
Lithuania	AB Siauliu Bankas.
Netherlands	ABN AMRO Bank; ING Groep; Van Lanschot Kempen.
Portugal	Banco BPI; Banco Comercial Português; Banco Espírito Santo.
Spain	Banco Bilbao Vizcaya Argentaria; Banco de Sabadell; Banco de Valencia; Banco Popular Español; Banco Santander; Bankia; Bankinter; CaixaBank; Liberbank; Unicaja Banco.
Slovakia	OTP Banka Slovensko; Tatra banka; Vseobecna uverova banka.

SOURCE: Own elaboration.

Annex 3 Results interacting observables with median assets dummy

Table A.3.1
Determinants of the COE by bank size

Variables	COE models							
	CAPM(1)	CAPM(2)	FF(1)	FF(2)	OJN(1)	OJN(2)	FH	FCFE
CET1 ratio								
* Small	-0.079	-0.078	-0.080	-0.091	0.177	0.232	-0.158*	-0.278
	(0.091)	(0.090)	(0.132)	(0.133)	(0.231)	(0.201)	(0.079)	(0.205)
* Large	-0.256***	-0.252***	-0.473***	-0.457***	-0.901***	-0.842***	-0.400***	-0.418*
	(0.077)	(0.076)	(0.102)	(0.104)	(0.181)	(0.198)	(0.144)	(0.226)
NPL ratio								
* Small	0.017	0.017	0.086	0.086	0.198**	0.286***	-0.146***	0.014
	(0.120)	(0.117)	(0.188)	(0.193)	(0.079)	(0.061)	(0.044)	(0.054)
* Large	0.105**	0.101**	0.204**	0.216***	0.194	0.294**	-0.003	0.235***
	(0.051)	(0.050)	(0.078)	(0.077)	(0.120)	(0.110)	(0.043)	(0.069)
Interbank deposit ratio								
* Small	0.077*	0.075*	0.107*	0.103*	0.160*	0.201**	0.041	0.279***
	(0.042)	(0.041)	(0.058)	(0.060)	(0.085)	(0.079)	(0.043)	(0.057)
* Large	-0.016	-0.018	-0.001	-0.003	0.199**	0.234**	-0.004	0.199***
	(0.028)	(0.028)	(0.051)	(0.048)	(0.098)	(0.102)	(0.041)	(0.050)
Cost-to-income ratio								
* Small	-0.023	-0.023	-0.037	-0.036	-0.013	-0.065	0.009	0.096**
	(0.026)	(0.026)	(0.026)	(0.027)	(0.064)	(0.047)	(0.014)	(0.047)
* Large	-0.005	-0.006	0.001	0.002	0.080	0.075	-0.034*	0.035
	(0.009)	(0.009)	(0.013)	(0.013)	(0.056)	(0.056)	(0.019)	(0.023)
Log (assets)								
* Small	0.467*	0.474*	0.574*	0.568*	-1.802***	-1.616***	-0.370	-1.013
	(0.241)	(0.239)	(0.296)	(0.297)	(0.427)	(0.454)	(0.407)	(0.769)
* Large	0.719***	0.721***	1.131***	1.066***	-0.653*	-0.703*	0.084	-0.613
	(0.167)	(0.167)	(0.229)	(0.233)	(0.379)	(0.365)	(0.245)	(0.366)
N bank-obs	880	880	881	881	655	670	914	795
N banks	57	57	58	58	38	39	50	49
Adjusted R2	0.569	0.558	0.631	0.628	0.415	0.456	0.321	0.407
Time-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

SOURCE: S&P Global Market Intelligence and devised by authors.
Note: Results from country-time FE regression. Each bank characteristic is interacted with a dummy that is equal to 1 if the average assets of the bank are equal to or larger than the median, and 0 otherwise. The coefficients are standard errors reported for "small" and "large" groups of banks. "Small" refers to banks with average assets below the median (dummy=0). "Large" refers to banks with average assets larger than or equal to the median (dummy=1). In CAPM and FF models, specifications (1) and (2) refer to the constant and time-varying cost of risk, respectively. OJN stands for the Ohlson and Juettner-Nauroth (2005) model, and specifications (1) and (2) refer to the exponential and simplified versions, respectively. FH stands for the Fuller Hsia (1984) model. FCFE stands for the free cash flow to equity model of Altavilla et al. (2021). Robust standard errors, clustered by bank, in parentheses. *** p<0.01, ** p<0.05, *p<0.1.

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