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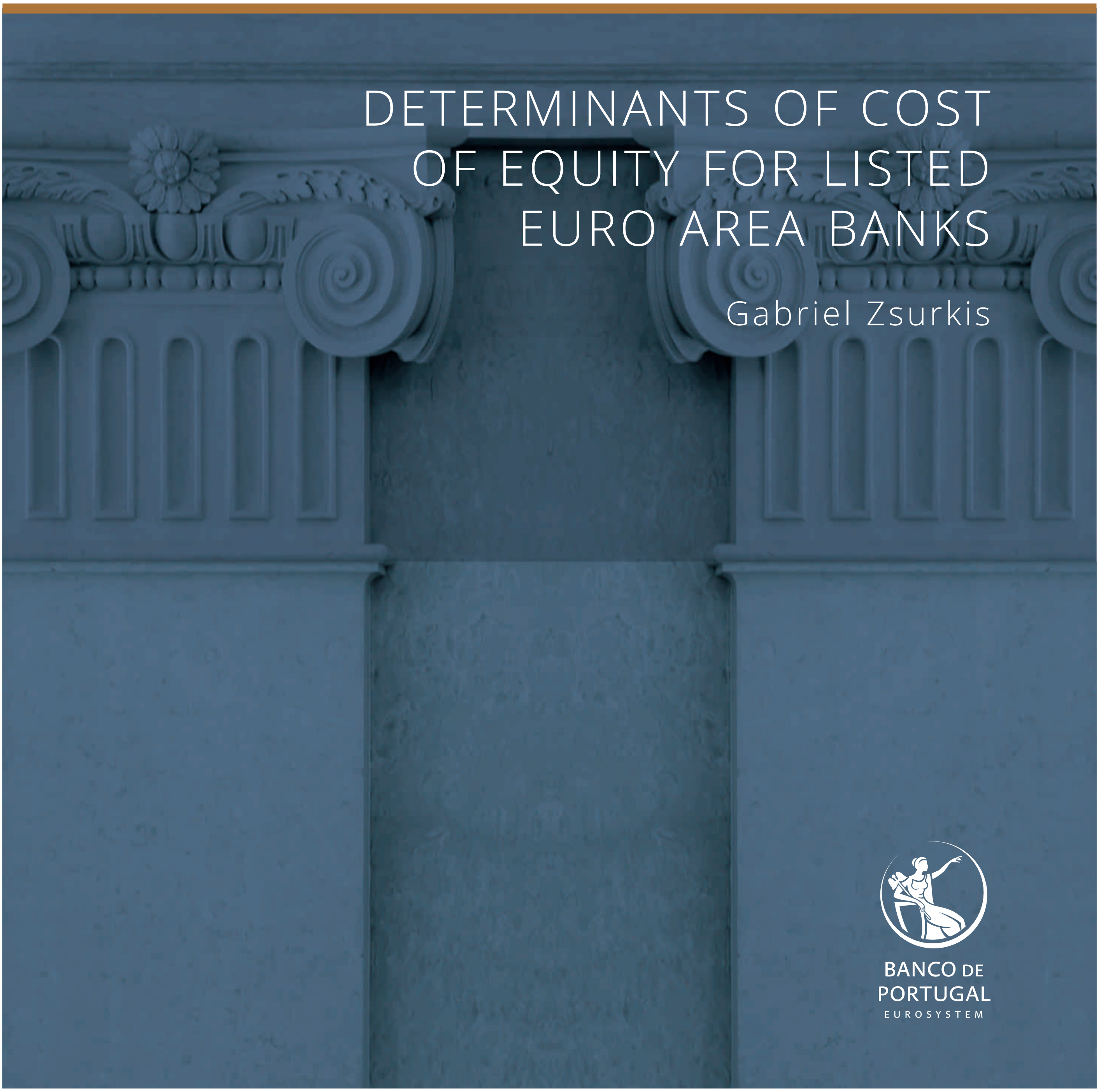

DETERMINANTS OF COST OF EQUITY FOR LISTED EURO AREA BANKS

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Determinants of cost of equity for listed euro area banks

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Abstract
The objective of this paper is to identify the banks' cost of equity determinants. We rely on a two-step approach. First, we estimate the cost of equity (COE) for listed euro area banks through multi-factor models, which are widely used in the asset pricing literature. We propose a new specification with overall market, banking sector and country risks and conclude that it has the best performance among all considered alternatives to mimic the bank's realized returns dynamics. Then, this specification is employed to estimate the banks' return sensitivities to each of the common risk factors and the COE. In the second step, we consider bank-specific and country-level variables and infer whether they explain the estimated COE time series dynamics and differences in COE across banks. We conclude that changes in ECB's interest rates and government bond rates were crucial to explain the evolution of the COE between 2012 and 2020. Moreover, we find that some variables related to business and financial cycles, and bank-specific variables such as Nonperforming Loan ratio, Tier1 ratio and Return on Assets are also important.

JEL: G20, G21, E44, G1

Keywords: cost of equity, monetary policy, financial stability.

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1. Introduction

Common equity capital is the most effective loss-absorption financial instrument. However, raising equity capital tends to be more expensive than debt financing: holding banks' equity carries a higher risk for investors and they expect to be rewarded through a combination of dividends and capital appreciation. Thus, bank's cost of equity is the expected return that an investor anticipates receiving for the equity share.

The cost that banks face to obtain extra equity capital is important for supervisory authorities, mainly because high costs of equity (COE) may threaten financial stability, especially when the COE is systematically above banks' return on equity (ROE)[1]. Banks that are not earning at least their corresponding COE have more incentive to take on additional risk (as they tend to increase their risk exposure through risky investments in search for higher profits) and are more vulnerable to liquidity runs, which may also cause contagion to other banks. On the other hand, reductions in COE led to bank lending expansions (see, for instance, Célérier *et al.* 2017), which may have a positive impact on the real economy (Buch and Neugebauer 2011).

Thus, the comparison between profitability or returns and cost of equity is crucial to properly assess the sustainability of banks' business model. However, unlike profitability measures like the return on equity (ROE) or the return on assets (ROA), COE is not observable and has to be estimated. The best way to estimate the COE is still not consensual since it measures investors' risk tolerance and expectations.

Similar to Altavilla *et al.* (2021)[2], we consider a two-step methodology: the first one estimates the COE for a subset of listed euro area banks and the second one links these estimates to bank fundamentals and country-specific macro and financial data. To estimate the COE, we consider the class of multi-factor models[3] developed in the asset pricing literature by, among others, Sharpe (1964), Fama and French (1993), Bessler and Kurmann (2014) and Fama and French (2015). The present work contributes to this literature by proposing two additional risk factors: a *banking sector risk* factor and a *country risk factor*. The first one is motivated by the documented fact that the factor models commonly used do not capture properly the variation in returns in the financial sector; see, for instance, Adrian *et al.* (2015) and Lafuerza and Mencía (2021). Regarding the second one, Griffin

1. Nowadays numerous euro area banks' ROE is still below the return required by their investors or COE (see, for instance, de Guindos 2019).

2. We do not address the third step of Altavilla *et al.* (2021)'s methodology, the extrapolation from listed to nonlisted banks.

3. We do not consider implied cost of capital models, as Altavilla *et al.* (2021), because the $I/B/E/S$ estimates are quite sparse for several euro area banks. Furthermore, Lafuerza and Mencía (2021) argue that the approach based on the analysts' forecasts yields rather noisy results, since forecasts tend to be more reliable for the whole market than for individual companies.

(2002) argues that the cost of capital calculations using multi-factor models are best performed on a within-country basis. Since the coefficients associated with the risk factors (betas) are possibly time-varying, we employ two parameter estimation methodologies that can capture this effect: the rolling window estimation and the Dynamic Conditional Beta approach proposed by Engle (2002, 2016).

In the second step, we investigate how the estimated COE depends, not only on profitability proxies and other bank-level variables, but also on euro area and country-level macro-financial variables. This second step may uncover alternative ways of reducing the gap between banks' COE and profitability, especially important in the present environment in which the euro area banking sector is facing low profitability and ongoing structural changes triggered by the global financial crisis and subsequent European sovereign debt crisis (see, for instance, BIS 2018).

Bank-specific variables can shape investors' perceptions of a bank's risk profile and the COE or expected return they require for investing in a bank's equity. For instance, balance sheet data, operating income and costs, the capital structure or even the bank size may explain differences in the COE across banks. Altavilla *et al.* (2021) present, for euro area listed banks, evidence of a plausible relationship between the COE dynamics and proxies of risk, efficiency, size and funding sources. Thus, for instance, supervisory authorities can use capital requirements measures and macro-prudential policy instruments to reduce the systemic risks and, consequently, the cost of equity. Baker and Wurgler (2015) and Belkhir *et al.* (2021) address the bank-capital-cost-of-equity relationship empirically, and the latter provide results suggesting that listed banks with higher equity ratios enjoy a lower COE. A likely explanation for this result is the premise that greater equity in the capital mix should lower equity risk, leading to decreases in stock-holders' required returns (Admati *et al.* 2013).

The COE are also influenced by the national business and financial cycles. For instance, it is easier for borrowers to repay their loans during an economic expansion and macroeconomic growth may also help in reducing the non-performing loan (NPL) ratios, which results in lower provisioning needs. Thus, the credit risk and consequently the COEs tend to be lower in good times. On the other hand, during recessions, investors will require higher returns in order to compensate the risk caused by increased defaults on loans and the consequent decline in profitability. Relevant contributions on the relationship between bank profitability and the business cycle were done by, among others, Albertazzi and Gambacorta (2009) and Bolt *et al.* (2012). Regarding the financial cycle, it is currently viewed as a key leading indicator of banking crises (see, for instance Borio 2012). Thus, macroprudential policies seek to smoothen the financial cycle in order to restrain excessive leverage or risk-taking, which contributes to reducing the banks' COE.

Furthermore, the ECB interest rates strongly influence the banking sector activity, namely the banks' profitability (Borio *et al.* 2017 and Altavilla *et al.* 2018), the banks' market valuation (Ampudia and van den Heuvel 2019) and, consequently, the COE. The ECB's monetary policy stance may also affect the banks' COE indirectly, through its effect on country-specific macroeconomic and financial indicators. For instance, the post-crisis accommodative monetary policy environment, also known as quantitative easing, substantially reduced the long-term government bond yields for several euro area countries (see, for instance, Falagiarda and Reitz 2015, Acharya *et al.* 2019, Alcaraz *et al.* 2019 and Pagliari 2021). This reduction in the sovereign credit risk was especially important for the financially distressed countries' banking sector. The mere prospect of a future default of the government complicates the financial intermediation (Bocola 2016), since banks that are exposed to risky government bonds are less able to borrow from capital markets, which may affect supply and increase the burden of re-financing existing loans, triggering a rise in NPLs (Boumparis *et al.* 2019).

Summing up, there are complex relationships and feedback loops between macroeconomic and bank-specific variables that must be taken into account in order to avoid biased estimates of the effects of these variables on the COE. Therefore, in contrast with Altavilla *et al.* (2021) and Belkhir *et al.* (2021), we consider a system of equations that is estimated using the three-stage least squares (3SLS) methodology of Zellner and Theil (1962), since this approach allows us to deal more straightforwardly than using traditional panel data models with two crucial issues that affect parameters estimation: (i) some bank-specific variables may be endogenously determined with the cost of equity and (ii) some bank and country-specific variables are persistent, which may also lead to biased coefficient estimates.

The remainder of the paper is organized as follows. Section 2 presents the methodologies employed to individually estimate the COE for euro area listed banks and the estimation results. Section 3 analyzes, in a longitudinal data framework, whether bank and country-specific covariates explain the variation of COE across banks and over time. Finally, Section 4 presents the main conclusions.

2. Cost of Equity estimation

The class of multi-factor models has at their core the mean-variance approach of Markowitz (1952) and Markowitz (1959). According to Markowitz's framework, in an efficient marketplace, higher returns are required for investors to take greater risks. Thus, the multi-factor models consider different sources of common risk exposure and allow us to decompose how much of the expected return is attributable to each common factor risk.

Assuming that the sensitivity to each risk factor is time-varying and the risk premia is time invariant, the multi-factor asset pricing models can be expressed as

$$COE = E(\tilde{R}_{i,t}) + rf_{it} = \boldsymbol{\beta}'_{i,t}\boldsymbol{\lambda} + rf_{it} \ , \qquad i = 1, ...N \, ; \, t = 1, ..., T \qquad (1)$$

where $\tilde{R}_{i,t}$ is the return of asset i at time t in excess of the risk-free rate and rf_{it} is the risk-free interest rate ; $\boldsymbol{\lambda}$ is the $(k \times 1)$ vector of risk premia[4] associated with the model's risk factors, with k being the number of risk factors, and $\boldsymbol{\beta}$ is the $(k \times 1)$ vector of beta coefficients estimated to measure the sensitivity to a given factor risk.

2.1. Estimation methods

In order to estimate the betas, the following linear specification is typically used:

$$\tilde{R}_{i,t} = \alpha_i + \boldsymbol{\beta}'_{i,t}\,\boldsymbol{f}_t + \varepsilon_{i,t} \ , \tag{2}$$

where $\boldsymbol{f}_t$ is a $(k \times 1)$ vector of risk factors (in excess of the risk-free interest rate) and α_i and $\varepsilon_{i,t}$, respectively, the regression constant and the iid residuals. The betas' time-varying nature is captured through the OLS estimation of rolling window regressions with window length equal to τ. That is, for each $t \geq \tau$, $\boldsymbol{\beta}'_{i,t}$ is estimated using (2) and data from $t - \tau$ to t.

Since the rolling regression approach assumes constant betas within the estimation window, the estimates may take some time to adjust to sudden changes in $\boldsymbol{f}_t$. The Dynamic Conditional Beta approach of Engle (2016) overcomes this drawback. This model is a variation of multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models, specifically developed to represent the dynamics of the conditional variances and covariances of financial time series (useful, for instance, to investigate volatility transmission and spillover effects). Thus, in this context, $\boldsymbol{\beta}_{i,t}$ are estimated in an indirect way, through the conditional variance-covariance matrix as follows:

$$\boldsymbol{\beta}_{i,t} = H^{-1}_{ff,t} H_{f\tilde{R},i,t} \ , \tag{3}$$

where $H_{ff,t}$ is the variance-covariance matrix of the risk factors and $H_{f\tilde{R},i,t}$ is the covariance between $\boldsymbol{f}_t$ and the excess return $\tilde{R}_{i,t}$. This approach allows for beta estimates to react instantaneously to changing market conditions. However, note that this approach assumes that the conditional mean is relatively unimportant for the realized returns and therefore, the analysis can be focused only on the conditional covariance matrix (see Engle 2016).

2.2. Risk factors

2.2.1. Widely used risk factors. The Capital Asset Pricing Model (CAPM) proposed by Sharpe (1964) and Lintner (1965), which postulates that the market risk is the only risk affecting expected security returns, has been a cornerstone

4. Risk premia or the price of risk is the return, in excess of the risk-free rate, required by investors to accept the exposure to common risks.

of the modern asset pricing theory. However, the CAPM model is not adequate in explaining abnormal returns. Consequently, the empirical research has been focused on identifying new pricing factors to deal with anomalies (empirical patterns that seem to challenge standard asset pricing theories).

Nowadays, a great number of papers on factors that attempt to explain the cross-section of expected returns are available[5] (see, for instance, Cochrane 2011 and Harvey *et al.* 2015). Based on this literature, we will consider the following widely used risk factors:

1. *Market*: investors expect a compensation for the financial market's risk exposure;
2. *Size*: small companies are inherently riskier and more volatile and investors expect to be compensated for taking on that additional level of risk;
3. *Value*: undervalued stocks should outperform overvalued stocks. A low price-to-book ratio means that the company is earning a very low return on its assets and a risk premium is required.
4. *Momentum*: stocks tend to maintain recent price trends in the near future; however, firms that have experienced a huge rise (fall) in returns recently should face a higher (lower) cost of capital because their investment opportunities have been adjusted.
5. *Profitability*: higher profitability attracts more competition, threatening profit margins and future cash flows. Thus, a risk premium is required for the additional risk.
6. *Investment*: high rates of investment are associated to low expected returns when controlling for value and profitability (Fama and French 2006). These findings suggest that a risk premium is required to buy stocks of firms that invest less;
7. *Sovereign credit risk*: a rational investor demands a higher compensation when default risk of sovereign debt is higher, since it can spillover to the financial and non-financial sectors, with a bearing on credit risk;
8. *Corporate credit risk*: closely related with sovereign credit risk; the expected stock returns are higher in times with higher credit risk (Friewald *et al.* 2014).

Fama and French (1993) propose a model that has three of the risk factors presented above: market, size and value. Carhart (1997) took the three-factor model and added a fourth factor, the momentum factor. More recently, in response to the evidence that Fama and French (1993)'s model ignores relevant risk factors (see, for instance, Novy-Marx 2013), Fama and French (2015) add profitability and investment factors to the three factors model.

Finally, an alternative to the CAPM model is the arbitrage pricing theory (APT) first presented by Ross (1976), which also considers macroeconomic factors. Recently, Altavilla *et al.* (2021) followed this approach and estimated a model with

5. Cochrane (2011) uses the expression "zoo of new factors".

three factors: market, sovereign credit and corporate credit risks. These factors directly affect banks' business activities and inherent risk exposures (Bessler and Kurmann 2014 consider similar factors and find that credit risk related factors are very important in explaining bank stock returns).

2.2.2. Two new risk factors. In addition to the aforementioned, we introduce two new risk factors:

1. *Banking sector risk*: the structural changes that took place in the euro area banking sector after the financial and sovereign debt crises affected the market sentiment about future bank profitability (see, e.g., BIS 2018). The lower than one price-to-book (P/B) ratios observed in the last decade also signal that markets have had pessimistic expectations about banks' realized returns, since depressed P/B ratios (see, for instance, Bogdanova *et al.* 2018) imply destruction of bank net asset value in the future. In this context, it is likely that investors will require a risk premium to invest in euro area banks' equity. Furthermore, the standard risk factors may impact differently financial and non-financial companies stocks' pricing. For instance, Adrian *et al.* (2015) documented that new risk factors are needed to properly capture variation in returns in the financial sector. In this work, we thus consider a euro area banks' equity index as a proxy for banking sector risk. Lafuerza and Mencía (2021) also consider a financial sector premium factor, measured as the difference between financial and non-financial indices' returns.
2. *Country risk*: By country risk we mean risk factors which have potential to affect all investments in a particular country simultaneously. As pointed out by Damodaran (2021), the exposure to risk can vary across countries based on country-specific particularities such as the economic growth life cycle, the economic structure or even political risks. In fact, there is some reported evidence that traditional multi-factor models like Fama and French (1993)'s models do not properly explain differences in expected returns across countries; for instance Griffin (2002) finds that these models are best estimated on a within-country basis. Moreover, Augustin *et al.* (2018) show that sovereign risk spillovers increase economic uncertainty and have more pronounced effects for financially distressed countries, as Ireland, Italy, Portugal and Spain during the sovereign debt crisis. In an efficient market, the country equity market capitalization incorporates all the relevant insights about sovereign risk, macroeconomic fundamentals and expectations about the future returns of its companies. Therefore, investors may demand country-specific equity risk premiums. Thus, we propose to consider the country's equity index as a proxy for country risk.

2.3. Data

Realized returns on listed euro area's banks equities. We started by identifying all listed banks with consolidated accounts and market capitalization above €1 billion.

For these banks, we obtained daily equity prices, total returns and the market capitalization series from Refinitiv Eikon. After taking into account the availability of the bank-level variables needed in the second step of our methodology, we are left with 28 euro area's listed banks from the period January 2011 to December 2020 (weekly frequency). Table 1 shows the number of banks considered by country and the weight that these banks represent in the total assets of the national banking sector in 2020.

	DE	ES	FI	FR	GR	IT	NL	PT
number of banks	3	6	1	3	2	10	2	1
% of the banking sector's total assets in 2020	26	80	66	70	47	80	51	21

Notes: DE, ES, FI, FR, GR, IT, NL and PT refer to, respectively, Germany, Spain, Finland, France, Greece, Italy, Netherlands and Portugal.

Table 1. Banks by country

Sources: Bloomberg and Banco de Portugal

Risk free interest rate. We consider the one-year euro overnight index swap (OIS) rate as a proxy to the risk-free interest rate (source: Refinitiv Eikon) .

Proxies for the risk factors.

- *Market risk* (MKT): Refinitiv Eurozone Price Return Index (source: Refinitiv Eikon) ;
- *Size, value, momentum, profitability and investment risk factors*:
  - *Size* or SMB (Small Minus Big) is the average return on the three smallest portfolios minus the average return on the three largest portfolios;
  - *Value* or HML (High Minus Low price-to-book) is the average return on the two value portfolios minus the average return on the two growth portfolios;
  - *Momentum* or MOM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios;
  - *Profitability* RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios;
  - *Investment* or CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios;

  The daily time series for the European market were downloaded from Kenneth French's data library, which also details the construction of these factors derived from a large sample of listed European firms. Adrian *et al.* (2015)

and Altavilla *et al.* (2021) also consider the Fama-French HML and SMB factors.

- *Sovereign* (SOV) and *Corporate credit risk* ($CORP$): we consider the risk factors from Altavilla *et al.* (2021):
  - *proxy* for *sovereign risk*: the difference in the return between equally-weighted Spanish, Italian and Portuguese total-return sovereign-bond indices and the equivalent German-bond index (all 7-10 years' residual maturity);
  - *proxy* for *corporate risk*: the difference in the return between euro-denominated total-return bond indices of BBB and AA-rated corporate bonds with a residual maturity of 7-10 years;

  All the data are from Refinitiv Eikon.
- *Banking sector risk* ($Banks$): we consider the price returns of the EURO STOXX Banks Index (SX7E) as a proxy for the banking sector risk (from Refinitiv Eikon). This factor was omitted for the banks included in this index in order to avoid endogeneity problem. However, preliminary analysis suggests that the banking sector risk is not statistically significant for the EURO STOXX Banks Index constituents; in this case, the market risk explains most of the changes in banks' realized returns.
- *Country risk factor* ($Country$): for each country, we consider the growth in market capitalization of their main equity index as a proxy for country risk; in order to avoid endogeneity problems, for a particular bank, its market capitalization is subtracted from the market capitalization of the country equity index (data from Refinitiv Eikon).

2.4. Factor models comparison

In this subsection we compare the goodness-of-fit of equation (2) for several model specifications, relying on the data presented in 2.3 from January 2011 to December 2020 (weekly frequency). Six different model specifications were considered:

i) *CAPM* model - considers only one factor, the market risk;
ii) *Fama-French (FF) three-factors* model - contains three risk factors: market, size and value;
iii) *Fama-French (FF) four-factors* model - considers four factors: market, size, value and momentum;
iv) *Fama-French (FF) five-factors* model - contains five risk factors: market, size, value, profitability and investment;
v) *Credit factors* model - it considers three factors: market, sovereign and corporate credit risk factors;
vi) *Banking and Country factors* model - includes the market factor and the two risk factors we propose: country and banking sector risk factors.

We start by estimating rolling regressions with time windows of 52 weeks (a year) and 104 weeks (two years) for each of the 6 models. We also consider two versions for each model specification and estimation methodology: one using the "original" factor series and one with orthogonalised factors[6], in order to eliminate correlations between them. Table 2 presents the average goodness-of-fit (R^2) across rolling regressions and banks for each country. Despite having good average goodness-of-fit, the $FF\ three\ factors$, $FF\ four\ factors$ and $FF\ five\ factors$ models suggest, for some banks, negative estimates for the COE. Thus, we will exclude these models. Moreover, the $Credit\ factors$ and $Banking\ and\ Country\ factors$ models perform better than the $CAPM$ in describing the excess return of stocks. Therefore, we only estimate the Dynamic Conditional Beta approach in (3) for these two specifications. The correlation between the realized and fitted returns is used as a proxy for the goodness of fit (an alternative to R^2).

Overall, the main findings using rolling regressions are: (i) there were structural breaks in all parameters - the estimated parameters (β) vary a lot across rolling windows; (ii) since not much is lost in terms of goodness-of-fit compared to the 104 weeks windows size case, time windows of 52 weeks are preferable as they result in CoE estimates that react quickly to changes in risk factors; and (iii) the CoE estimates vary widely with model specifications, which illustrates the complexity of estimating expected returns already reported in the literature.

Regarding the Dynamic Conditional Beta approach, we highlight the following insights: (i) as expected, the COE obtained using this methodology respond very quickly to the risk factors (the beta estimates are much more volatile); and (ii) as with rolling regressions, the COE estimates are also extremely model-dependent here.

We select the methodology that explains a greater part of the variations in returns (see 2.4) and result in COE values that do not contradict economic intuition. For instance, the $FF\ three\ factors$, $FF\ four\ factors$ and $FF\ five\ factors$ models are excluded since they suggest, for some banks, negative estimates for the COE.

Therefore, the results presented in Tables 2 and 3 suggest that the specification we propose with market, banking sector and country equity risks estimated using the Dynamic Conditional Beta methodology is the one that performs better among all considered alternatives. Therefore, we will consider for each listed bank the CoE estimates obtained using this approach[7].

6. As in Altavilla *et al.* (2021), we orthogonalise by sequentially regressing factors onto each other and constructing the orthogonalised factor from the residual.

7. Note that both country and banking sector risks represent additional risk relative to the market risk. Hence, the two factors were orthogonalised: (i) banking sector factor is regressed on the market risk factor; and the residuals are used in the Dynamic Conditional Beta model; (ii) the country factor is regressed on both banking sector and market risks factors and, once again, the resulting residuals are used as risk factors.

	1st quartile	**2nd quartile**	**3rd quartile**	**4th quartile**	**All**
$CAPM$	0.32	0.28	0.42	0.50	0.38
$FF\ three\ factors$	0.34	0.40	0.54	0.63	0.48
$FF\ four\ factors$	0.44	0.42	0.57	0.67	0.53
$FF\ five\ factors$	0.45	0.45	0.60	0.69	0.55
$Credit\ factors$	0.40	0.37	0.49	0.57	0.46
$Banking\ and\ Country\ factors$	0.46	0.53	0.53	0.59	0.53

Notes: 1^{st} quartile , 2^{nd} quartile , 3^{rd} quartile and 4^{th} quartile include, respectively, banks with total assets between the minimum and 1st quartile, between the 1st quartile and 2nd quartile, between the 2nd quartile and the 3rd quartile and between the 3rd quartile and the maximum of the empirical distribution of total assets considering all banks; average CoE across rolling regressions and banks for a given country for the time period 2012-2020; time windows of 52 weeks, orthogonalized risk factors.

Table 2. Rolling regressions - average R^2 by bank size

	1st quartile	**2nd quartile**	**3rd quartile**	**4th quartile**	**All**
$Credit\ factors$	0.62	0.55	0.70	0.75	0.66
$Banking\ and\ Country\ factors$	0.70	0.67	0.75	0.77	0.72

Notes: 1^{st} quartile , 2^{nd} quartile , 3^{rd} quartile and 4^{th} quartile include, respectively, banks with total assets between the minimum and 1st quartile, between the 1st quartile and 2nd quartile, between the 2nd quartile and the 3rd quartile and between the 3rd quartile and the maximum of the empirical distribution of total assets considering all banks; "R^2" is the average correlation between the realized and fitted returns for a given country; the risk factors were orthogonalized.

Table 3. Dynamic Conditional Beta - average "R^2" by bank size

2.5. Expected risk premiums (ERP) calculations

As in Altavilla *et al.* (2021), we consider the historical time series average of the respective risk factor as estimates for the $\boldsymbol{\lambda}$ vector of risk premiums in (1). This approach is consistent with the notion that the risk premia have, implicitly, a long term perspective. According to Cochrane (2011), "...large variation in risk premia implies exciting changes for macroeconomics...". Table 4 displays the estimated expected risk premiums (ERP) associated with the risk factors in 2.2 .

	MKT	SMB	HML	MOM	RMW	CMA	SOV	CORP
ERP(%)	5.45	2.48	3.32	14.55	6.23	2.22	1.44	1.55

Notes: **MKT** - market; **SMB** - size; **HML** - value; **MOM** - momentum; **RMW** - profitability; **CMA** - investment; **SOV** - sovereign credit; **CORP** - Corporate credit.

Table 4. Estimated ERP (λ)

For some of the risk factors, the average of the historical return's time series has been negative for the last 10/15 years. A negative risk premium means that shareholders expect to lose money investing in stocks, which contradicts economic theory. Thus, in order to obtain positive values for the risk premiums, we consider daily data from January 1999 to December 2020 to estimate the risk premiums (data prior to 1999 is not available for several risk factors). However, we still get negative averages for the returns of the banking sector and country risk, and therefore, these two risk premiums will be calculated in alternative ways. Table 5 presents the ERP for the banking sector risk and for the country equity risk. We detail below the employed approach to estimate them.

Banking sector risk premia. The EURO STOXX Banks Index (SX7E) had annual growth rates of -6.5% and -4.6% for, respectively, 1999-2020 and 2012-2020 time spans. Given the structural changes that this sector faced in the aftermath of the 2008 crisis, one would expect an additional banking sector risk premia to be added to the market risk premia when investing in banks' equity. In order to infer this possibility we consider:

$$Banks_t = \alpha + \beta_{banks}\widetilde{RM}_t + \eta_t$$

where $Banks_t$ is the difference between a banking sector equity index returns and the risk-free interest rate and $\widetilde{RM}_t$ is the market excess return. Since $\hat{\beta}_{banks} \approx 1.28$, there is statistical evidence that banking sector is riskier than the overall market. Thus, we use $(\hat{\beta}_{banks} - 1)\times$ *market risk premia* (MKT from Table 4) as a proxy for the banking sector risk additional premia.

Country risk premia. The country risk premia is also difficult to estimate, since the national equity index market capitalization has negative annualized growth for some countries between 1999 and 2020. Thus, we propose an indirect way to estimate the country equity risk premia, based on countries' 5-year government Credit Default Swaps (CDS) (obtained from Refinitiv Eikon). Let the country's sovereign risk premia be equal to the average (from 1999 to 2020) of the difference between *Country's mid spread* and *Germany's mid spread* CDS. Since, in the short term, the country equity risk premium is likely to be greater than the country's default spread[8], we multiply the sovereign risk premia by the ratio *country's equity index standard deviation/euro area's equity index standard deviation*, when this ratio is greater than one (country's equity market riskier than euro area's overall equity market). When overall equity market is riskier than country's equity market, the sovereign risk premia is considered as a proxy for country risk premia.

Table 5 shows that investors require higher risk premia to invest in some countries. The model estimations suggest that risk sensitivity (β) to variations in the national equity index is positive and far from zero for almost all countries. However, it will affect the COE in an asymmetric way across countries, since risk premium is particularly high only for few of them. Regarding banking sector risk, it also seems relevant in explaining changes in bank's realized returns.

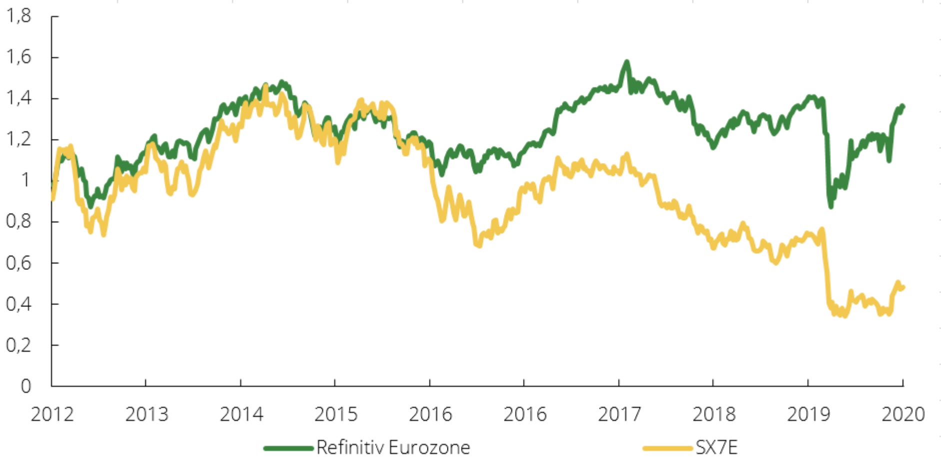
	Banks	**Countries**							
		DE	ES	FI	FR	GR	IT	NL	PT
ERP (%)	1.55	-	1.17	0.00	0.27	8.36	1.54	0.06	2.55

Table 5. Estimated ERP (λ) - banking sector and country risk factors

2.6. Selected Cost of Equity time series

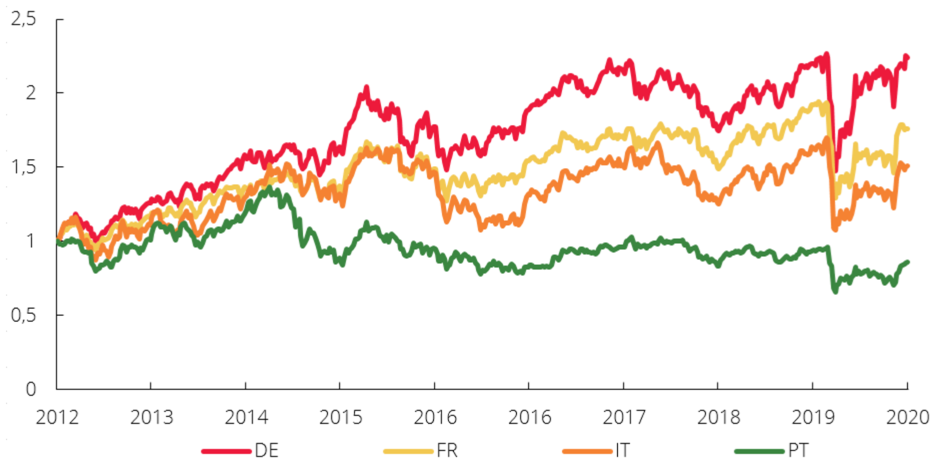
Figures 1 and 2 illustrate the time series employed to compute the price returns used as risk factor proxies. Figure 1 shows the euro area banking sector's index and the broad euro area market's index performances and suggests that banks underperformed the rest of the market since 2016. In this context, the cost of equity for euro area banks tends to be higher. Additionally, Figure 2 shows relevant differences in performance across national stock indexes. Again, investing in countries with lower growth rate of stock prices may require higher expected returns.

8. The rationale behind this statement is the fact that equity risk premia reflects both sovereign and corporate credit risk. However, it is commonly believed that corporate bond yields are subject to sovereign "floors"- that is, corporate yields would generally be higher than sovereign yields (see, for instance, Bedendo and Colla 2015).



Notes: Jan2012=1, weekly data. SX7E - EURO STOXX Banks Index and Refinitiv Eurozone Price Return Index.

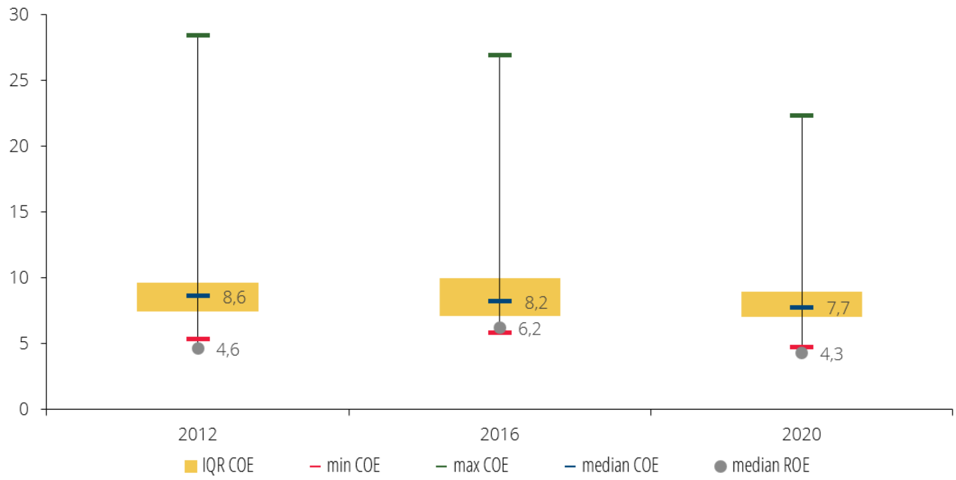
Figure 1: Overall and banking sector indexes - country and banking sector risk factors



Notes: Jan2012=1, weekly data.

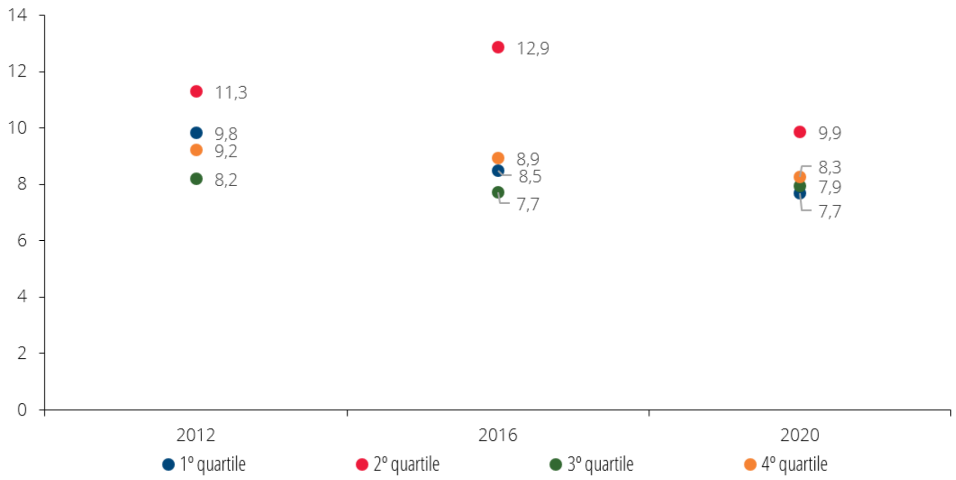
Figure 2: National stock indexes - country risk factor

Figure 3 presents the dispersion of the estimated COE among the 28 banks considered. The median COE and interquartile range are lower when 2020 is compared with 2012 and 2016. The median ROE grew 1.6 p.p. between 2012 and 2016, but faced a signficant decrease in 2020, caused by the outbreak of COVID-19.



Notes: IQR COE, min COE, max COE and median COE refer, respectively to the interquartile range, minimum, median and maximum of the banks' COE by year; median ROE is the median by year of the variable *normalized* ROE provided by Bloomberg.

Figure 3: Dispersion of the selected COE estimates



Notes: *1st quartile*, *2nd quartile*, *3rd quartile* and *4th quartile* include, respectively, banks with total assets between the minimum and 1st quartile, between the 1st quartile and 2nd quartile, between the 2nd quartile and the 3rd quartile and between the 3rd quartile and the maximum of the empirical distribution of total assets considering all banks.

Figure 4: Estimated CoE by quartile of total assets (%)

Figure 4 displays the estimated COE averaged by quartiles of the total assets distribution for 2012, 2016 and 2020. The banks included in the second quartile seem to face a higher COE throughout this period.

Summing up, the banks' COE estimates[9] are obtained from a factor model with market, banking sector and country equity risks using the Dynamic Conditional Beta approach of Engle (2016) in (3). Overall, the fitted time series for each bank seem to reproduce well variations in the realized returns (see Table 3), which suggests that a great part of bank's expected return component or COE is being captured.

3. Cost of equity determinants

We estimated the COE using stock market data, which fully reflects all known information under the efficient market assumption. Therefore, different risk sensitivities (β) across banks are possibly explained by country and bank-specific data reflected in banks' equity price. In this section we intend to infer which macro-financial variables and banks' fundamentals are important in explaining changes in banks' COE.

Beyond Euro-area wide key variables such as ECB interest rates, which have a huge impact on the banking sector activity (see, for instance, Borio *et al.* 2017 and Altavilla *et al.* 2018), there are also many country-specific macroeconomic and financial indicators that may influence bank' market valuation and cost of equity.

3.1. Country-level variables

Data related with national business and financial cycles may provide important insights, especially in a context where the concerns about the euro area business cycle synchronization and convergence towards common cycles were amplified after the financial crisis and the subsequent European sovereign debt crisis. In fact, similar business cycles across countries is one of the requirements of an optimal currency area (see, e.g., McKinnon 1963). However, Ferroni and Klaus (2015) find evidence that this requisite is violated. They documented compelling evidence of an asymmetric behavior of Spanish fluctuations relative to the Euro area one. More recently, Belke *et al.* (2017) conclude that synchronization of economic activity between the core (Germany, France, Austria, Finland and the Netherlands) and the financially distressed countries (Portugal, Italy, Ireland, Greece and Spain) fell markedly after the financial crisis, possibly caused by the higher sovereign risk premia that the financially distressed faced. Moreover, they also present evidence supporting that individual countries have business cycles of different amplitudes.

In contrast to business cycles, no obvious "natural" measure is available for the financial cycle, currently viewed as a key leading indicator of banking crises (see, for instance, Borio 2012). Conceptually, financial cycles differ from business through their amplitude and frequency. That is, financial cycles evolve over the medium

9. Quarterly averages of the estimated weekly COE were considered since macro and balance sheet data are not available at higher frequency.

term - the completion of full peak-to-trough cycles may last up to decades (see, e.g., Aikman *et al.* 2015) - and may be described in terms of cyclical movements in private-sector credit and property prices (Drehmann *et al.* 2012). Rünstler *et al.* (2018) estimate financial cycles in EU countries and assess their properties and their relationship to business cycles. One of their main conclusions is that there are important differences across countries in the properties of cycles in credit and house prices.

Moreover, the sovereign debt crisis, which affected the euro area economies in a different degree, may have deepened the differences in business and financial cycles across countries. For instance, Augustin *et al.* (2018) argue that companies headquartered in financially distressed countries (Ireland, Italy, Portugal and Spain) suffer relatively more from a rise in sovereign credit risk than companies outside these countries. Bocola (2016) finds that the mere prospect of a future default of the government complicates financial intermediation, since banks that are exposed to risky government bonds are less able to borrow from capital markets and, consequently, to finance firms. In turn, the increase in sovereign risk also reduces the willingness of financial intermediaries to hold claims of the private sector.

Against this background, and after some preliminary analysis, we consider the following macroeconomic and macro-financial variables associated with the national business and financial cycles and sovereign risks:

- business cycle proxies - data from OECD
  - i country's quarterly GDP growth rates (percentage change from previous quarter and change from same quarter of previous year);
  - ii country's yearly GDP gap (deviations of actual GDP from potential GDP as a percentage of potential GDP);
  - iii country's quarterly unemployment rate (percentage);
  - iv euro area's yearly GDP gap (deviations of actual GDP from potential GDP as a percentage of potential GDP);
- credit cycle proxies - data from BIS
  - i country's quarterly credit-to-GDP ratio (% of GDP);
  - ii country's quarterly credit gap (actual - HP filter trend, % of GDP);
  - iii country's real residential property prices (Index,2010=100; year-on-year and quarterly changes, in percentage);
- sovereign credit risk proxies - data from OECD
  - i country's 10-year government bonds interest rates (percentage).
- euro area reference risk-free rates from Refinitiv:
  - i 3-months Euro overnight index swaps[10];
  - ii 6-months Euro OIS;
  - iii 1-year Euro OIS.

10. For instance, Iskrev *et al.* (2021) argue that the Overnight Index Swap (OIS) rates are good proxies of the reference risk-free rates in the euro area.

3.2. Bank-specific variables

Banks' sensitivity to each of the common risk factors (market, country and banking sector), and, consequently, the COE may depend on bank fundamentals, since these bank-specific factors influence the investors' perception of banks' risk profile. In order to infer whether there is statistical evidence supporting this statement, we consider bank-level variables derived from bank balance sheet and income statement information and also regulatory capital ratios (as in Altavilla *et al.* 2021 and Belkhir *et al.* 2021).

For that, we consider quarterly data from Bloomberg, focusing only on variables that have few missing values in the timespan 2012Q1-2020Q4, namely: (1) Nonperforming Loans/Total Loans; (2) Tier1 Capital Ratio; (3) Loans/Deposits; (4) Provision for Loan Losses/Total Loans; (5) Loans/Total Assets; (6) Cash and Marketable Securities/Total Assets; (7) Operating Margin; (8) Total Debt/Total Assets; (9) Long term Debt to Total Equity; (10) Long term Debt to Total Assets; (11) Interbank Assets/Total Assets; (12) Operating Income/Total Assets; (13) Risk-Weighted Assets; (14) Tangible Common Equity to Risk-Weighted Assets; (15) Net Interest Margin; (16) Return on Assets.

3.3. Methodology

Properly estimating the effects of country- and bank-specific factors on banks' COE contributes to a better assessment of threats to financial stability. The related literature, such as Altavilla *et al.* (2021) and Belkhir *et al.* (2021), consider panel data models in this context. A primary motivation for using panel data is to solve the omitted variables problem: if characteristics that are correlated with both dependent and explanatory variables are omitted, the regression coefficients estimates will be biased, due to endogeneity. Thus, the key issue here is whether the unobserved individual effects are uncorrelated with the explanatory variables: random effects models assume that there is no correlation and fixed effects imply that there is something within the individual that may impact the predictors or outcome variables. The economic interpretation of the individual effects suggests that they are probably correlated with the explanatory variables, since relevant country-specific information, possibly related with differences in economic structures and institutions (and also qualitative insights related with banks' business model or corporate values) may be omitted in practice. On the other hand, the random effects model can be viewed as a regression model with a random constant term. However, it is hard to justify, in practice, why are the individual effects being treated as random and uncorrelated with the regressors. Altavilla *et al.* (2021) estimate panel regressions with random effects (RE) and also with fixed effects (FE). Belkhir *et al.* (2021) only consider fixed effects intending to control for any country-and time-specific factors that may affect banks' COE.

In this paper, we do not consider the traditional panel data specifications. Instead, the three-stage least squares (3SLS) methodology of Zellner and Theil

(1962) will be used, since it allows us to deal more straightforwardly with the endogeneity (some bank-specific variables may be endogenously determined with the cost of equity) and persistent regressors issues (some bank and country-specific variables seem persistent, which may also lead to biased coefficient estimates). In order to circumvent the endogeneity problem, Belkhir *et al.* (2021) instrument the bank capital measures with their averages. However, to the best of our knowledge, there is no literature related to this work concerned with the potential biases in the relevant coefficient estimates due to the use of persistent variables as regressors. For instance, important bank-specific indicators such as total assets or non-performing loans do not seem to have a stationary behavior (mean-reverting dynamics), at least following the 2008 financial crisis.

In order to illustrate how the use of persistent regressors can lead to biased estimates, let us consider the bivariate system

$$\begin{aligned} y_t &= \delta x_t + u_t, \qquad t = 0, ..., T \\ x_t &= \rho x_{t-1} + \varepsilon_t, \end{aligned}$$

where y_t represents the COE for a given bank and x_t the non-performing loan (NPL) ratio. Rinaldi and Sanchis-Arellano (2006), Louzis *et al.* (2012) and Cerulli *et al.* (2020) find that country-specific factors like unemployment, output growth and inflation are key determinants of NPLs and suggest that this indicator of realized credit risk displays strong autoregressive structure (or is even non-stationary). Moreover, since there may be omitted variables that influence both COE and NPL ratio, u_t and ε_t are probably correlated. Thus, when ρ is close to unity and the regression disturbance correlated with the regressor's innovation, the estimation of δ faces Stambaugh (1999)'s bias problem. The bias of the OLS estimate of δ depends on the correlation between u_t and ε_t. If Cor$(u_t, \varepsilon_t) < 0$, $\hat{\delta}$ is upward biased; on the other hand, $\hat{\delta}$ is downward biased when Cor$(u_t, \varepsilon_t) > 0$. Hjalmarsson (2007) show that the Stambaugh bias raises similar econometric issues in a panel data setting.

This problem becomes much more complex in a multiple predictor model where several bank and country-specific predictors with strong autoregressive behavior are simultaneously considered. A possible way to avoid the estimates' bias problem is to take into account these interactions between variables considering a system of equations. We consider some restrictions in order to limit the number of parameters to be estimated and, thus, reduce parameter estimates uncertainty. Firstly, starting with the set of country-specific variables presented in 3.1, we perform some preliminary analysis. After taking into account issues like (near-) multicollinearity and the theoretical and empirical (measured through correlation analysis and statistical significance in some exploratory regressions) relevance to predict COE, a subset of important country-level variables is selected; we consider a maximum lag length of four for all the regressors. A similar approach is employed to select a subset of key bank-specific variables for the COE. Regarding the dummy variables, we iteratively eliminate those that are not significant in each equation.

3.4. Modelling steps and the selected specification

The preliminary analysis described above suggests that the following predictors, some of them transformations of the variables presented in 3.1 and 3.2, are important for estimating the CoE :

- euro-area wide and country-level variables
  i OIS_3M - 3-months euro overnight index swap;
  ii GOV - 10-year government bonds yield;
  iii $spread\_GDP$ - the difference between the country's and euro area's year on year GDP growth;
  iv $credit\_GDP\_gr$ - credit-to-GDP growth relative to the previous quarter, in percentage points;
  v res_pr_gr - the year-on-year change in real residential property prices
- bank-specific variables
  i ROA - Return on assets;
  ii NPL - Nonperforming Loans/Total Loans ratio;
  iii $Tier1$ - Tier1 Capital Ratio;
  iv $assets$ - Total Assets.

Figures 5 and 6 show that are marked differences between countries for two of the considered country-level variables. Portugal and Greece grew well below the euro area average until 2016, Italy and Greece diverged for most of the 2012-2020 period, while France and Germany present values closer to the euro area average between 2012 and 2020. Regarding the growth of credit-to-GDP ratio ($credit\_GDP\_gr$), Portugal, Spain and Italy had, with the exception of 2020, mostly negative credit-to-GDP growth rates, in contrast to France and, to some extent, Germany.

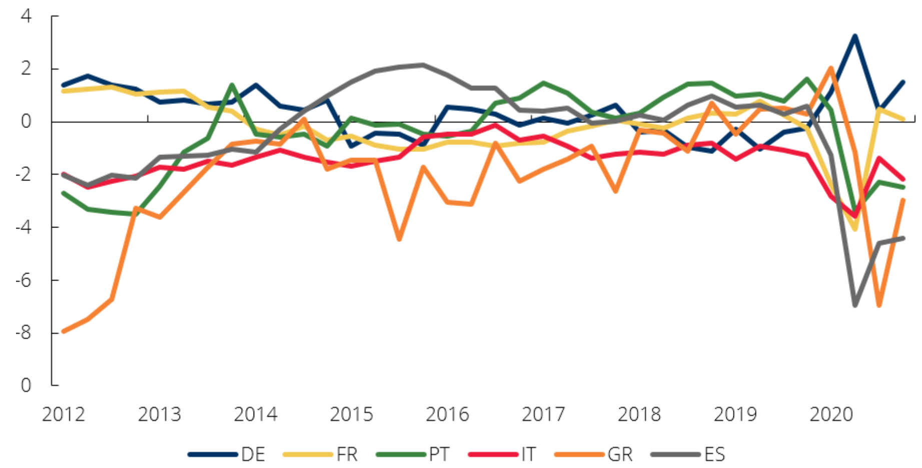


Figure 5: Difference between country's and euro area's GDP growth (%) ($spread\_GDP$)

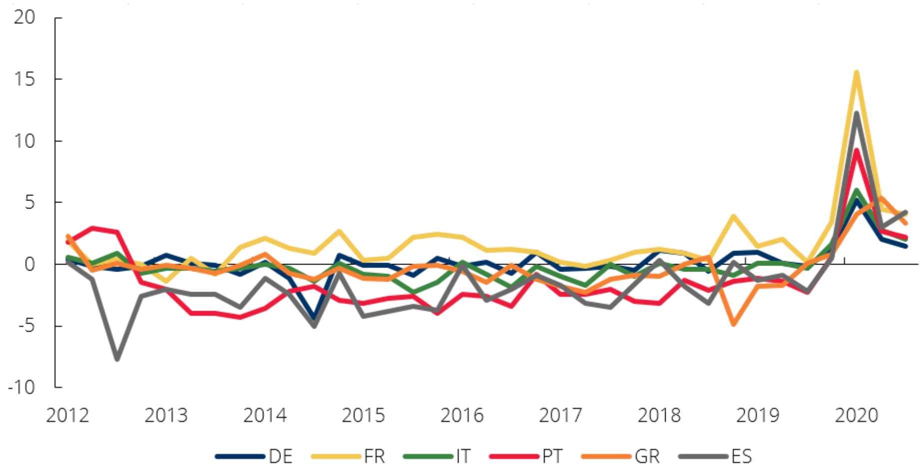


Figure 6: Credit-to-GDP growth (p.p) ($credit\_GDP\_gr$)

Figure 7 illustrates the time dynamics over 2012-2020. Overall, Nonperforming Loans / Total Loans (%) (NPL) had an upward trend until 2016, followed by a rather sharp downward trend which led this ratio reach minimum values in 2020. On the other hand, the Return on Assets (%) (ROA) and Tier 1 Capital ratio (%) ($Tier1$) show upward trends between 2012 and 2020. However, for ROA, this positive path seems to be interrupted in 2020.

Considering the variables presented above, we adopt a bottom-up approach similar to the one suggested by Lütkepohl (2007), which starts from analyzing a

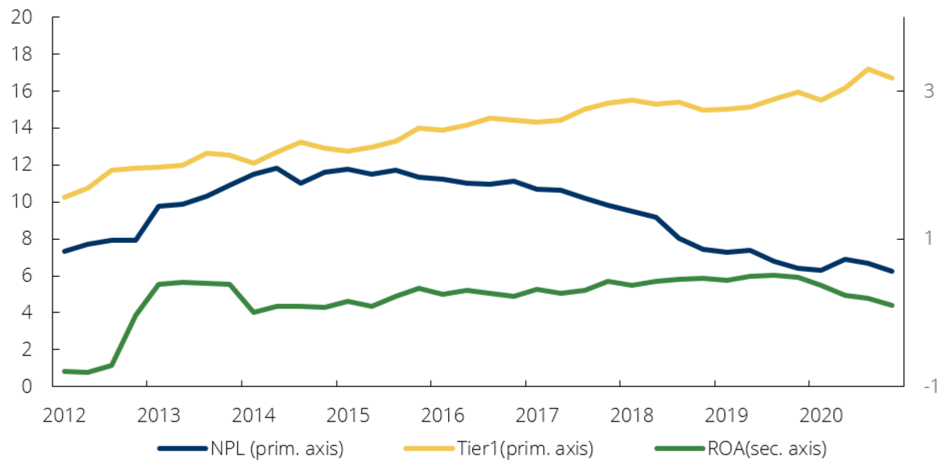


Figure 7: Bank-specific variables (%)

Notes: Arithmetic mean considering all banks; NPL, $Tier1$ and ROA refer, respectively, to the Nonperforming Loans / Total Loans ratio (%), Tier 1 Capital ratio (%) and Return on Assets (%).

small group of variables and uses the results from that analysis to construct a larger and more complete model. Thus, the successive extensions to the initial system of equations can be used to study the robustness of the main parameters' estimates. Table 6 presents the estimated coefficients for the CoE's equation from three system of equations. The first one only considers interest rates. Then, business and financial cycle proxies are also included; and finally, the third system of equations considers interest rates, business and financial cycle proxies and bank-specific variables.

Interest rates. We start by considering two key financial variables to explain the COE, namely, the 3-months euro overnight index swap (OIS_3M)[11] and 10-year government bonds interest rates (GOV). In response to the deterioration in financial and economic conditions in 2011 and early 2012, one of the major unconventional central bank intervention was triggered by the ECB's President Mario Draghi "whatever it takes" speech on July 23, 2012. The ensuing accommodative monetary policy environment, also known as quantitative easing, substantially reduced the long-term government bond yields for several euro area countries, improved banks' lending conditions and boosted the stability of the overall Euro area financial system (see, for instance, Falagiarda and Reitz 2015, Acharya *et al.* 2019, Alcaraz *et al.* 2019 and Pagliari 2021). In recent years, the

11. We also considered 6-months and 1-year Euro overnight index swaps (OIS), but 3-months Euro overnight index swaps (OIS) seems to have more pronounced statistical significance.

policy rates reached the zero lower bound and there is no well-defined instrument providing and encompassing of a central bank's unconventional policy stance (Pagliari 2021). Despite being aware of their limitations as proxies for the monetary policy stance between 2012 and 2020, we consider the risk-free interest rates (overnight index swaps) reasonable for our purpose.

Then, we first consider a restricted system of the form:

$$\begin{cases} COE_{i,t} = \alpha'\, TD_t + \boldsymbol{\zeta}'\, BD_i + \kappa' CD_j + \delta_1 GOV_{i,t} + \delta_2\, OIS\_3M_{i,t} + u_{i,t,1}, \\ OIS\_3M_{i,t} = \alpha_1'\, TD_t + \sum_{l=1}^{3} \varphi_{1,l}\, OIS\_3M_{i,t-l} + u_{i,t,2}, \\ GOV_{i,t} = \alpha_2'\, TD_t + \kappa_2'\, CD_j + \sum_{l=1}^{3} \varphi_{2,l}\, GOV_{i,t-l} + \delta_{2,1}\, OIS\_3M_{i,t} + u_{i,t,3}, \end{cases} \tag{4}$$

at time t; *TD* is a matrix of time dummies, where each column contains a time dummy, and α, α_1 and α_2 are vectors of parameters associated with each column of *TD*; *BD* is a matrix with all the bank dummies in columns and ζ is a vectors of parameters associated with each column of *BD*; *CD* is a matrix of country dummies where each column contains a country dummy and κ and κ_2 are vectors of parameters associated with each column of *CD*; GOV is the 10-year government bond yield and OIS_3M is the 3-months euro overnight index swap (OIS).

Although our main focus is on the first regression of the system (4), the other two regressions are important to take into account the persistent dynamics of OIS_3M and GOV and also to infer whether the ECB's interest rates influence the government bonds' interest rates. Regarding the time dummies, we consider quarterly dummies for 2020, in order to accommodate the unexpected shock caused by the COVID-19 pandemic outbreak. For the U.S., Bretscher *et al.* (2020) show that spread of COVID-19 had a negative and significant impact on firm equity valuations and Ke (2021) find that firms experienced an increase in the cost of equity during the pandemic. Regarding the impact of the pandemic on banking sector, please see Aldasoro *et al.* (2020) and EBA (2020). Finally, country and bank-level dummies were also considered aiming to capture differences in the COE's mean which are not explained by the explanatory variables. We remove all dummies variables that are not significant at the 10% level in (4).

The 3SLS estimation in Table 6 indicates that $\hat{\delta}_1$ and $\hat{\delta}_2$ are both statistically significant at the 1% significance level (see Table 6, first column): (i) there is a positive relationship between government bonds' interest rates (GOV) and the COE and (ii) COE is lower for higher values of the euro area's risk-free rate proxy (OIS_3M). This last result may be related with the transmission of the monetary policy on bank profitability. For instance, Borio *et al.* (2017) and Claessens *et al.* (2018) find a positive relationship between interest rates and bank net interest margins for a large sample of banks. Additionally, Claessens *et al.* (2018) state that this relationship is nonlinear, with the low interest rates having a significantly greater impact on banks' net interest margins than the higher interest rates. Thus, it is difficult for banks to maintain their income if low interest rate environments persist for many years; and lower profitability increases the vulnerability to shocks and declines in market confidence, which is reflected in higher cost of equity.

Moreover, $\hat{\delta}_{2,1}$ in the third equation of system (4) is also statistically significant at 1% level and has a positive sign, suggesting that ECB's interest rates were important at lowering government bond yields. Finally, for the dummy variables estimates we conclude: (i) the time dummy associated with the beginning of the pandemic (2020Q1) is only statistically significant for OIS_3M's equation; (ii) the time dummy 2020Q2 is statistically significant at 1% level and negative for CoE's equation, and statistically significant at 1% level and positive for GOV's equation; (iii) the country dummies reveal differences in the government bonds' mean across countries but only the one associated with Greece is statistically significant and positive for COE's equation; and, finally, (iv) the bank-specific dummies, proxies for the fixed effects, are only statistically significant (and negative) for some relatively small Italian and Spanish banks.

	System (4)	**System (5)**	**System (6)**
OIS_3M	-1.790***	-1.762***	-3.153***
GOV	0.596***	0.499***	0.481***
$spread\_GDP$		- 0.185**	-0.223***
$credit\_GDP\_gr$		-0.141***	-0.131***
NPL			0.059***
ROA			-0.873***
$Tier1$			-0.136***
Obs.	893	893	893
"$R - squared$ "	0.758	0.759	0.783

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 6. Estimated parameters for the COE's equation

Starting from the specification discussed above, we will now add business and credit cycle variables. After some preliminary analysis, we choose the difference between the country's and euro area's year on year GDP growth, called $spread\_GDP$, and the quarterly credit-to-GDP's growth in percentage points, named $credit\_GDP\_gr$. It is expected a negative relationship between COE and these two covariates.

Thus, a more complete system of the form

$$
\begin{cases}
COE_{i,t} = \alpha' \, TD_t + \zeta' \, BD_i + \kappa' \, CD_j + \delta_1 GOV_{i,t} + \delta_2 \, OIS\_3M_{i,t} + \\
\delta_3 \, spread\_GDP_{i,t} + \delta_4 \, credit\_GDP\_gr_{i,t} + u_{i,t,1}, \\
OIS\_3M_{i,t} = \alpha_1' \, TD_t + \sum_{l=1}^{3} \varphi_{1,l} \, OIS\_3M_{i,t-l} + u_{i,t,2}, \\
GOV_{i,t} = \alpha_2' \, TD_t + \kappa_2' \, CD_j + \sum_{l=1}^{3} \varphi_{2,l} \, GOV_{i,t-l} + \delta_{2,1} \, OIS\_3M_{i,t} + u_{i,t,3}, \\
spread\_GDP_{i,t} = \alpha_3' \, TD_t + \kappa_3' \, CD_j + \varphi_{3,1} \, spread\_GDP_{i,t-1} + u_{i,t,4}, \\
credit\_GDP\_gr_{i,t} = \alpha_4' \, TD_t + \kappa_4' \, CD_j + \sum_{l=1}^{2} \varphi_{4,l} \, credit\_GDP\_gr_{i,t-l} \\
+\delta_{4,1} \, OIS\_3M_{i,t} + \delta_{4,2} \, gdp\_gap\_ue + u_{i,t,5},
\end{cases}
\tag{5}
$$

was estimated, where gdp_gap_ue is the deviation of the euro area's GDP from potential GDP (output gap), considered as exogenous variable; and $credit\_GDP\_gr$ is the credit-to-GDP growth relative to the previous quarter, in percentage points . For the COE's equation, we reintroduce all the bank-level and country dummies and retest their statistical significance.

Let us first focus on the first regression of the estimated system (5); see Table 6. The coefficients associated with the business and credit cycle proxies, respectively, $spread\_GDP$ and $credit\_GDP\_gr$ are statistically significant (at 5% and 1% level, respectively) and have negative signs.

That is, the COE tends to be lower for banks in countries with above average output growth (for positive values of $spread\_GDP$). A growth in credit provision, proxied by $credit\_GDP\_gr$, has a similar effect on risk perception. The inclusion of these two variables do not interfere with the statistical significance of OIS_3M and GOV. There is statistical evidence that the COE's unconditional mean is much higher for Greece. These results are not shown in Table 6.

The $credit\_GDP\_gr$'s equation provides some relevant insights (these results are omitted in Table 6 to save space). Both $\hat{\delta}_{4,1}$ and $\hat{\delta}_{4,2}$ are statistically significant at 1% and have negative coefficients. That is, the credit-to-GDP growth is higher when the euro area's GDP is below its potential and the short term interest rates (OIS_3M) are low or negative.

Interest rates, business and credit cycle proxies and bank-specific variables. The system in (5) is augmented with the inclusion of bank-specific variables. We choose three important variables that provide statistical significance across different preliminary model specifications, namely: (i) the return on assets (ROA) as a proxy for profitability, (ii) the Tier 1 capital ratio ($Tier1$) and (iii) the NonPerformingLoansto/TotalLoans ratio (NPL) as a proxy for realized credit risk. We take the euro area and country-level variables as exogenous; their regressions are only included in the system of equations to avoid biased estimates caused by the use of persistent regressors (see Stambaugh 1999 and Hjalmarsson 2007). In turn, we take into account the possibility that COE, ROA, $Tier1$ and NPL are jointly and endogenously determined.

After excluding the statistically insignificant variables, we obtain:

$$\begin{cases} COE_{i,t} = \alpha' \, \mathsf{TD}_t + \boldsymbol{\zeta}' \, \mathsf{BD}_i + \kappa' \mathsf{CD}_j + \delta_1 GOV_{i,t} + \delta_2 \, OIS\_3M_{i,t} \\ +\delta_3 \, spread\_GDP_{i,t} + \delta_4 \, credit\_GDP\_gr_{i,t} \\ +\theta_1 ROA_{it} + \theta_2 Tier1_{it} + \theta_3 NPL_{it} + u_{i,t,1}, \\ OIS\_3M_{i,t} = \alpha_1' \, \mathsf{TD}_t + \sum_{l=1}^{3} \boldsymbol{\varphi}_{1,l} \, OIS\_3M_{i,t-l} + u_{i,t,2}, \\ GOV_{i,t} = \alpha_2' \, \mathsf{TD}_t + \kappa_2' \, \mathsf{CD}_j + \sum_{l=1}^{3} \boldsymbol{\varphi}_{2,l} \, GOV_{i,t-l} + \delta_{2,1} \, OIS\_3M_{i,t} + u_{i,t,3}, \\ spread\_GDP_{i,t} = \alpha_3' \, \mathsf{TD}_t + \kappa_3' \, \mathsf{CD}_j + \boldsymbol{\varphi}_{3,1} \, spread\_GDP_{i,t-1} + u_{i,t,4}, \\ credit\_GDP\_gr_{i,t} = \alpha_4' \, \mathsf{TD}_t + \kappa_4' \, \mathsf{CD}_j + \sum_{l=1}^{2} \boldsymbol{\varphi}_{4,l} \, credit\_GDP\_gr_{i,t-l} \\ +\delta_{4,1} \, OIS\_3M_{i,t} + \delta_{4,2} \, gdp\_gap\_ue + u_{i,t,5}, \\ NPL_{i,t} = \alpha_5' \, \mathsf{TD}_t + \boldsymbol{\zeta}_5' \, \mathsf{BD}_i + \kappa_5' \mathsf{CD}_j + \sum_{l=1}^{2} \boldsymbol{\varphi}_{5,l} \, NPL_{i,t-l} \\ \boldsymbol{\delta}_{5,1} GOV_{i,t} + u_{i,t,5}, \\ ROA_{i,t} = \alpha_6' \, \mathsf{TD}_t + \boldsymbol{\zeta}_6' \, \mathsf{BD}_i + \kappa_6' \mathsf{CD}_j + \sum_{l=1}^{2} \boldsymbol{\varphi}_{6,l} \, ROA_{i,t-l} \\ +\delta_{6,1} NPL_{i,t} + \delta_{6,2} (OIS\_1Y - OIS\_3M) + u_{i,t,6}, \\ Tier1_{i,t} = \alpha_7' \, \mathsf{TD}_t + \boldsymbol{\zeta}_7' \, \mathsf{BD}_i + \kappa_7' \mathsf{CD}_j + \sum_{l=1}^{3} \boldsymbol{\varphi}_{7,l} \, Tier1_{i,t-l} \\ \psi_{7,1} \, COE_{i,t} + \delta_{7,1} \, OIS\_3M_{i,t} + \delta_{7,2} \, NPL_{i,t} + u_{i,t,7}, \end{cases} \tag{6}$$

where NPL is the ratio Nonperforming Loans/Total Loans, ROA is the Return on Assets and $Tier1$ is the Tier 1 Capital Ratio.

The third column of Table 6 presents the estimates for the COE's equation: ROA, NPL and $Tier1$ ratios are highly statistically significant (at 1% level).

Higher profitability (ROA) and capital ratio ($Tier1$) seem to reduce investor's risk perception and consequently the bank's COE, while a higher NPL has an opposite effect. These findings are in line with, for instance, those of Altavilla *et al.* (2021) and Belkhir *et al.* (2021). The inclusion of these three variables do not interfere with the statistical significance of OIS_3M, GOV, $spread\_GDP$ and $credit\_GDP\_gr$ in the first equation of the system (5). Moreover, there are also some interesting results not shown in Table 6: (i) there are no statistically significant time dummies; (ii) only the country-dummy associated with Greece is statistically significant and positive (the COE is, on average, 13 percentage points higher for Greek banks); and (iii) for seven banks, the bank-specific dummies are statistically significant and six of them have negative coefficient. Thus, it seems that only the explanatory variables we consider are not sufficient to explain the extremely high COE faced by Greek banks.

The remaining equations of (6) provide relevant insights about the bank-specific variables' dynamics (the results are not shown in Table 6 to save space):

- GOV *equation*: higher OIS_3M is associated with higher government bond rate (GOV);
- $credit\_GDP\_gr$ *equation*: overall, OIS_3M and the gap between euro area's actual and potential output (gdp_gap_eu) have a negative relationship with the growth of the credit-to-GDP ratio;
- NPL *equation*: higher 10-year government bond yields (GOV) are associated with higher NPL ratios ($\hat{\delta}_{5,1} = 0.201$ and statistically significant at 1%level), which seems to be in line with Boumparis *et al.* (2019)'s statement that "sovereign rating downgrades trigger bank rating downgrades which in turn lead to a reduction in lending supply and, at the same time, increase the burden of re-financing existing loans, therefore, triggering a rise in NPLs";
- ROA *equation*: high NPL ratios are a drag on banks' profitability ($\hat{\delta}_{6,1} = -0.013$ and statistically significant at 1%level), since greater loan loss provisions are required (see, for instance, Bogdanova *et al.* 2018). We also considered $(OIS\_1Y - OIS\_3M)$ as a proxy for the slope of the yield curve: $\hat{\delta}_{6,2} = 1.100$ and statistically significant at 1%level, which suggests that a steeper yield curve boosts profitability. Borio *et al.* (2017) find that the level of interest rates is also important and is positively related with the steepness of the yield curve, but we do not find statistical evidence that the interest rates variables in levels affect the COE. However, some authors argue that the monetary policy's actions net impact on bank profitability is ambiguous (see, e.g., Alessandri and Nelson 2015, Borio *et al.* 2017, Altavilla *et al.* 2018, Eggertsson *et al.* 2019 and Rostagno *et al.* 2019).
- $Tier1$ *equation*: the first and last equations of the system suggest that there is simultaneity between CoE and $Tier1$; a higher $Tier1$ ratio decreases the CoE but there also seems to be an opposite effect of smaller magnitude which associates higher CoE with higher $Tier1$ ratio; $\hat{\theta}_2 = -0.140$ in the first equation versus $\hat{\psi}_{7,1} = 0.094$ in the eighth equation of system (6). These

results seem to agree with the findings reported by other works. Following the 2008/09 global financial crisis, extensive regulatory reforms have boosted bank capital and liquidity. Increasing capital requirements limits bank risk taking and default risk (see, for instance, Bahaj and Malherbe 2020) and may result in lower COE. Regarding the negative effect of the OIS_3M on $Tier1$, seems in line some literature that associates a higher policy rate with lower capital ratios (see, for instance, Couaillier 2021). By pushing ECB's policy rates to record low levels, the recent expansionary monetary policy helped the banks to increase the ratio of equity capital to total assets, since the substantial funding cost relief makes the equity less risky and, consequently, the increases in capital ratios are less costly.

3.5. Robustness checks

In this section, we perform some robustness checks by investigating whether our main findings remain valid when: (i) the systems of equations are estimated for different subsamples; (ii) some variables are added and others removed; and (iii) specifications with no autocorrelation in error terms are considered.

We consider three subsamples: two of them consider 2014 as starting year, which was marked by the worsening of the medium-term outlook for inflation in the context of policy rates close to their effective lower bound. In response to this threat, the ECB announced the commitment to use both non-standard and standard measures in order to avoid a prolonged period of too low inflation (see, for instance, Neri and Siviero 2019). In addition, we also estimated the system of equations (6) with data up to 2019 in order to infer whether excluding data from 2020 substantially changes the parameter estimates, since some works documented that the COVID-19 crisis have had a particularly negative impact on banking sector (see, for instance, Özlem Dursun-de Neef and Schandlbauer 2021, Borri and di Giorgio 2021, Demirgüç-Kunt *et al.* 2021 and N Berger *et al.* 2021).

Table 7 presents the parameter estimates for the COE equation of system (6) across the three subsamples. The NPL ratio is not statistically significant after 2014. Another relevant insight from Table 7 is the increased importance of the ROA for the bank's COE determination after 2014; the parameter estimates are more than 50% greater (in absolute value) when 2012-2019 and 2012-2020 are compared with 2014-2019 and 2014-2020.

	All obs.	2012:2019	2014:2020	2014:2019
OIS_3M	-3.154***	-3.082***	-3.517***	-3.587***
GOV	0.481***	0.403***	0.612***	0.590***
$spread\_GDP$	-0.223***	-0.404***	-0.262***	-0.525***
$credit\_GDP\_gr$	-0.131***	-0.118**	-0.155***	-0.171***
NPL	0.059***	0.057***	0.035	0.016
ROA	-0.873***	-0.840***	-1.384***	-1.392***
$Tier1$	-0.136***	-0.151***	-0.140***	-0.166***
Obs.	893	782	768	657
"$R-squared$ "	0.783	0.784	0.769	0.767

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 7. Subsamples estimation: estimated parameters for the COE's equation of system (6)

We also investigate whether the parameter estimates change substantially when slightly different specifications are considered for the COE's equation in (6). Six additional bank-specific variables were included: (i) the natural logarithm of total assets (log_assets) as a proxy for bank size; (ii) interbank assets / total assets (int_bank_assets), which reflects banks' overall portfolio risk diversification; (iii) total equity/ total assets ($Equity/Assets$) as a measure of a bank's financial leverage; (iv) net interest margin (net_int_mg) and (v) operating income/total assets ($op\_inc/assets$), as proxies for profitability; and (vi) total deposits/total assets ($dep/assets$) as a measure of liquidity (high values for this ratio means more stable funding structure, which would reduce its susceptibility to liquidity problems).

Table 8 presents the estimates. The main objective of this exercise is to infer the robustness of NPL, ROA and $Tier1$ estimates. Overall, the coefficients associated with these bank-specific variables do not change considerably and continue highly statistically significant (at 1% level) across the specifications.

The second column of Table 8 shows that the coefficients associated with NPL, ROA and $Tier1$ remain statistically significant when the macro-variables are excluded from system (6); nonetheless, the goodness-of-fit is lower, which insinuates that country-level data helps to explain banks' COE dynamics. The estimates associated with log_assets (please see 3rd and 4th columns) are not statistically significant. Thus, there does not appear to be a linear relationship between the bank size and the COE. Column (5) reveals that $Equity/Assets$ does not work better than $Tier1$ as capital measure. Moreover, int_bank_assets is statistically significant at 1% level and has negative estimated coefficient. Higher interbank assets / total assets (int_bank_assets) reduces bank's overall portfolio risk through diversification and, therefore, promotes a reduction in the COE. Then, column (6) shows that $op\_inc/assets$, an alternative to ROA as proxy for profitability, is statistically significant when ROA is excluded (this result does not hold if these two variables are included). Finally, the last column of Table 8 reveals that $dep/assets$ is statistically relevant when $Tier1$ is omitted; otherwise, the nullity of the coefficient associated with $dep/assets$ cannot be rejected.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OIS_3M	-3.154***		-3.020***	-3.247***	-2.632***	-2.923***	-2.826***
GOV	0.481***		0.485***	0.485***	0.541***	0.443***	0.563***
$spread\_GDP$	-0.223***		-0.183***	-0.210***	-0.182***	-0.180***	-0.159**
$credit\_GDP\_gr$	-0.131***		-0.185**	-0.123**	-0.090**	-0.098***	-0.119***
NPL	0.059***	0.090***	0.103***	0.100***	0.111***	0.093***	0.091***
ROA	-0.873***	-0.335**	-0.504***	-0.487***	-0.463***		-0.432***
$Tier1$	-0.136***	-0.165***	-0.121***	-0.135***		-0.146***	
log_assets			-0.049	-0.040			
int_bank_assets					-0.022**		
$Equity/Assets$					-0.038		
net_int_mg				-0.163			
$op\_inc/assets$						-1.068***	
$dep/assets$							-1.107**
Obs.	893	893	893	794	893	893	893
"$R-squared$"	0.783	0.770	0.781	0.783	0.776	0.781	0.781

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 8. Alternative covariates: estimated parameters for the COE' equation of system (6).

The time dimension is a key feature when longitudinal data is used and we have to take into account issues like serial correlation and dynamic effects. Since it is difficult to identify the effects of serial correlation in $u_{i,t,k}$ (k stands for the equation number within a system) on parameter estimates and t-statistics when the complex system of equations in (6) is considered, we also estimated specifications for which none of the residual terms exhibit autocorrelation. To this end, we use the Shehata (2011)'s STATA module $LMAREG3$.

Table 9 presents the parameter estimates for the COE's equation in systems (4), (5) and (6) augmented with lags of the dependent variable. The COE time series exhibits relevant autocorrelation, with the sum of the autoregressive coefficients between 0.44 and 0.53. Overall, the bank-specific and macro variables presented in Tables 6 and 7 are still statistically significant, but their coefficients are considerably lower (in absolute value). Finally, starting from the specification presented in the third column of Table 9, we perform some additional robustness checks.

The analysis of Table 10 allow us to draw similar conclusions to those obtained from Table 7, including the increased importance of the ROA for the bank's COE determination after 2014, higher coefficient estimates (in absolute value) for $spread\_GDP$ when 2020 is omitted. Finally, the results reported in Table 11 are in line with those presented in Table 8 .

	System (4)	System (5)	System (6)
$l.COE$	0.678***	0.677***	0.630***
$l2.COE$	-0.156***	-0.159***	-0.199***
OIS_3M	-1.162***	-1.125***	-2.024***
GOV	0.363***	0.308***	0.338***
$spread\_GDP$		-0.132**	-0.140**
$credit\_GDP\_gr$		-0.074**	-0.067**
NPL			0.038**
ROA			-0.418***
$Tier1$			-0.079***
Obs.	893	893	893
"$R - squared$"	0.839	0.839	0.850

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 9. Without error autocorrelation: estimated parameters for the COE's equation

	All obs.	2012:2019	2014:2020	2014:2019
$l.COE$	0.630***	0.644***	0.677***	0.699***
$l2.COE$	-0.199***	-0.203***	-0.242***	-0.254***
OIS_3M	-2.024***	-2.179***	-2.283***	-2.551***
GOV	0.338***	0.314***	0.450***	0.494***
$spread\_GDP$	-0.140**	-0.230**	-0.164***	-0.275***
$credit\_GDP\_gr$	-0.067**	-0.027	-0.084**	-0.061
NPL	0.038**	0.031*	0.025	0.010
ROA	-0.418***	-0.409***	-0.730***	-0.746***
$Tier1$	-0.079***	-0.107***	-0.086***	-0.121***
Obs.	893	782	768	657
"$R - squared$"	0.850	0.853	0.847	0.850

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 10. Subsamples estimation without error autocorrelation: estimated parameters for the COE's equation of system

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$l.COE$	0.630***	0.648***	0.630***	0.633***	0.613***	0.640***	0.636***
$l2.COE$	-0.199***	-0.170***	-0.200***	-0.207***	-0.185***	-0.202***	-0.195***
OIS_3M	-2.024***		-1.914***	-2.092***	-1.772***	-2.013***	-1.746***
GOV	0.338***		0.312***	0.309***	0.358***	0.317***	0.364***
$spread\_GDP$	-0.140**		-0.126**	-0.141**	-0.139**	-0.139**	-0.116***
$credit\_GDP\_gr$	-0.067**		-0.059*	-0.090**	- 0.070**	-0.062*	-0.066*
NPL	0.038**	0.052***	0.034**	0.031*	0.058***	0.044***	0.049***
ROA	-0.418***	-0.312***	-0.465***	-0.460***	-0.316***		-0.434***
$Tier1$	-0.079***	-0.089***	-0.092***	-0.106***		-0.093***	
log_assets			-0.104*	-0.099			
int_bank_assets					-0.017**		
$Equity/Assets$					-0.077**		
net_int_mg				-0.169			
$op\_inc/assets$						-1.007***	
$dep/assets$							-0.388
Obs.	893	893	893	794	893	893	893
"$R-squared$"	0.850	0.845	0.850	0.850	0.846	0.848	0.847

Notes: Dummy variables are not presented; */**/*** indicates statistical significance at the 10/5/1% levels, respectively.

Table 11. Alternative covariates without autocorrelation: estimated parameters for the COE's equation

4. Conclusions

In this paper, we rely on a two-step approach (similar to Altavilla *et al.* 2021) in order to shed some light on the banks' cost of equity determinants. In the first step, financial market data are used to estimate the banks' COE. More precisely, we consider multi-factor models with a wide set of risk factors commonly used in asset pricing literature and also introduce two alternative risk factors: one intending to infer whether investors require an additional risk premium to invest in euro area banks' equity (banking sector risk) and another, called country risk, that tries to capture if the risk exposure perception varies across countries, for instance, due to different economic structures or due to the existence of macroeconomic imbalances in some countries. The specification we propose - with overall market, country equity and banking sector risks - estimated using the Dynamic Conditional Beta approach of Engle (2016) is the one that performs better in reproducing variations in banks' realized returns. Therefore, we use for each of the 28 euro area banks considered in our sample, the COE estimates obtained using this approach.

Then, in the second step, the estimated COE is used as dependent variable. As regressors, we consider several macro-financial and bank level variables. Unlike Altavilla *et al.* (2021) and Belkhir *et al.* (2021), which consider traditional panel data specifications, we consider the three-stage least squares (3SLS) methodology proposed by Zellner and Theil (1962) to estimate simultaneous equation since it allows us to deal more straightforwardly with the endogeneity and persistent regressor issues. Regarding the covariates, we consider euro area reference risk-free rates, government bond interest rates, business and financial cycles proxies, and a wide set of bank-level variables from balance sheet, income statement and also regulatory capital ratios.

Overall, this work confirms the importance of some macroeconomic, financial and bank-specific data in explaining variations in the investor's risk perception. It also illustrates the usefulness of the systems of equations in this context, since some of the variables considered have both direct and indirect statistically significant effects on the COE. The estimated equations suggest that banks in countries with above average output growth face lower COE. We also find mild statistical evidence that the credit to output growth instigates a reduction in the cost of equity. This somehow counterintuitive result may have caused by the inversion of the credit to output ratio downward trend in the last years of the sample (Antoshin *et al.* 2017 find evidence of post financial crisis creditless recoveries in economies that experienced a credit boom prior to the financial crisis), which coincided with a general reduction in the COE. Moreover, the return on assets (ROA), the non performing loan ratio (NPL) and the Tier 1 capital ratio ($Tier1$) are also important in explaining differences in COE between euro area banks. Notwithstanding, this work also finds statistical evidence that the dynamics of these three key indicators depend on the evolution of the ECB's policy rates and of the government bond's interest rates.

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