EUROPEAN CENTRAL BANK

EUROSYSTEM

Occasional Paper Series

Carlo Altavilla, Paul Bochmann,
Jeroen De Ryck, Ana-Maria Dumitru,
Maciej Grodzicki, Heinrich Kick,
Cecilia Melo Fernandes, Jonas Mosthaf,
Charles O'Donnell, Spyros Palligkinis

Measuring the cost of equity of euro area banks

No 254 / January 2021

Contents

Abstract

The cost of equity for banks equates to the compensation that market participants demand for investing in and holding banks' equity, and has important implications for the transmission of monetary policy and for financial stability. Notwithstanding its importance, the cost of equity is unobservable and therefore needs to be estimated. This occasional paper provides estimates of the cost of equity for listed and unlisted euro area banks using a three-step methodology. In the first step, ten different models are *estimated*. In the second step, the models' results are *combined* applying an equal-weighting procedure. In the third step, the combined costs of equity for individual banks are *aggregated* at the euro area level and according to banks' business models. The results suggest that, since the Great Financial Crisis of 2007-08, the premia that investors demand to compensate them for the risk they bear when financing banks' equity has been persistently higher than the return on equity (ROE) generated by banks. We show that our estimates of cost of equity have plausible relationships to banks' fundamentals. The cost of equity tends to be higher for banks that are riskier (higher non-performing loan ratios), less efficient (higher cost-to-income ratio), and with more unstable funding sources (higher relative reliance on interbank deposits). Finally, we use bank fundamentals to estimate the cost of equity for unlisted banks. In general, unlisted banks are found to have a somewhat lower cost of equity compared to listed banks, with business model characteristics accounting for part of the estimated difference.

JEL codes: G20, G21, E44, G1

Keywords: cost of equity, monetary policy, financial stability, banking supervision

Non-technical summary

The cost of equity for banks equates to the compensation that market participants demand for investing and holding banks' equity and it has important implications for the transmission of monetary policy and for financial stability. Understanding how costly equity capital is for euro area banks is useful for policymakers for several reasons. First, it is important for the transmission of monetary policy. In cases where the cost of equity exceeds banks' profitability outlook, their ability to attract capital may be hindered. That in turn might adversely affect banks' intermediation capacity. Second, it is significant for financial stability, as a high cost of equity and the resulting limitations on raising new capital may prevent banks from building up buffers against negative shocks. Third, it is important for regulators and supervisors, as it will help them to calibrate and understand the impact of prudential policies, and carry out assessments of financial stability. Supervisors may use estimates of banks' cost of equity, together with their returns on equity, when assessing business model sustainability. In the light of this, they need an independent benchmark of cost of equity to assess whether banks' internal processes and policies are sound, and their lending decisions sufficiently prudent.

However, unlike the cost of debt, the cost of equity is not directly observable and therefore needs to be estimated. This paper provides estimates of the cost of equity for listed and unlisted euro area banks using a three-step methodology. The results show that the implied premia that investors demand as compensation for the risk they bear when holding banks' equity has been persistently higher than the return on equity generated by banks since the onset of the 2008 financial crisis. Differences in regulatory treatment and bank strategies related to retained earnings may significantly influence this value.

This paper also finds that banks' estimated cost of equity is related to the fundamentals of the banks and that the shape of that relationship is in line with economic theory. Banks holding more non-performing loans have a higher cost of equity, reflecting the elevated credit risk that they are exposed to. Similarly, banks relying more heavily on the less stable wholesale funding market and banks that are less cost-efficient also face a higher cost of equity.

The cost of equity appears to be somewhat lower for unlisted banks than for listed banks, partly reflecting differences in business models. The lower cost of equity for unlisted banks is to some extent explained by the presence of government-owned promotional and development banks in the sample of unlisted banks. Such institutions tend to be less risky than other banks and, given their public policy objectives, the government shareholder may expect them to generate lower returns. Among other banks, there is no systematic difference between the cost of equity of commercial, savings, and cooperative unlisted banks.

These conclusions are relevant for prudential policy as well as for monetary policy. As banks need to earn their cost of equity to attract external capital, the results show that banks need to take action to sustainably decrease the gap between return on equity and cost of equity. This might be achieved by reducing operational inefficiencies, which may entail up-front costs but would both improve profitability and durably reduce the cost of equity in the longer run. Moreover, banks need to make sure that their pricing of risk associated with the loans they extend and the funding sources they choose is appropriate.

1 Introduction

The cost of equity (COE) for banks equates to the compensation that market participants demand for investing and holding banks' equity and has important implications for the transmission of monetary policy and financial stability. Understanding how costly equity capital is for euro area banks is important for policymakers for several reasons. First, it is important for the transmission of monetary policy. In the cases where the cost of equity exceeds banks' profitability outlook, their ability to attract capital may be hindered. That in turn may adversely affect banks' intermediation capacity, as scarce capital limits their capacity to provide credit, potentially increasing borrowing costs for the private sector and harming the real economy (e.g. Altavilla et al. 2018; Girotti and Horny, 2020; Boucinha et al. 2017). This is particularly relevant for the euro area, where the private sector relies predominantly on banks for its financing. Second, it is important for financial stability, as a high cost of equity and the consequent limitations for raising new capital may prevent banks from building up buffers against negative shocks. Third, it is important for regulators and supervisors, as it will help them calibrate and understand the impact of prudential policies, and carry out assessments of financial stability (e.g. Kovner, 2019). Supervisors may use estimates of banks' cost of equity together with their returns on equity in assessing business model sustainability. Furthermore, changes in the factors determining the cost of equity may reflect the views of market participants about the economic outlook and could therefore serve as an indicator of the expected state of the economy (see European Central Bank, 2018). In the light of this, supervisors and central banks need an independent benchmark of COE to assess whether banks' internal processes and policies are sound, and whether the lending decisions are sufficiently prudent.

However, unlike the cost of debt, the cost of equity is not directly observable and therefore needs to be estimated. Equity does not generate a fixed stream of contractual payments, nor does it have a direct cost in the accounting sense. More specifically, the cost is related to the future stream of dividends and capital gains which shareholders may benefit from, and therefore must be inferred from other (observable) prices and quantities filtered through an econometric model. However, large-parameter and estimation uncertainty associated with model estimates may undermine the potential use of the COE to derive policy provisions.

In general, a proxy for the cost of equity can be found by either using (ex post) realised stock returns or employing an (ex ante) measure implied from analyst earnings projections. Recent studies show that the implied (ex ante) cost of equity might be a better measure of the cost of capital than realised returns (see Pastor et al., 2008; Bekaert and Harvey, 2000; Hail and Leuz, 2006). However, many studies (Adrian et al. 2015; Fama and French, 1997; Bernes and Lopez, 2006; Kings, 2009) employ the ex post realised measure to estimate the cost of equity. Overall, whether the cost of equity is better captured by the ex ante or ex post measure is an empirical question. In the present study, instead of relying on a single methodology, we use and combine several different approaches in an attempt to maximise the potential information content coming from the various approaches.

This paper provides estimates of the cost of equity for listed and unlisted euro area banks using a three-step methodology. The first step (*the estimation step*) consists of estimating the cost of equity for each bank in the sample using a set of models that differ in terms of the amount of information used and the degree to which this information is forward-looking. The second step (*the combination step*) uses model combination techniques to average the results of the individual models across each bank. Finally, the third step (*the aggregation step*) generates results at various levels of cross-sectional aggregation using market capitalisation (for listed banks) or the book value of equity (for unlisted banks) of individual banks as weightings in the weighted averaging procedure.

The structure of the paper is as follows. The paper starts with a description of the estimates of the cost of equity reported by banks through supervisory surveys (Section 2), pointing to the heterogeneity of such internal estimates. It then introduces the empirical methodologies for estimating the cost of equity for listed banks, and discusses the results obtained with the individual approaches (Section 3). Section 4 discusses the model combination technique and the aggregation step, and presents the estimates of the euro area aggregate cost of equity. It also links the estimates to bank fundamentals. The methodology and results for unlisted banks' cost of equity are then presented in Section 5. Finally, Section 6 provides some robustness checks, and Section 7 sets out the conclusions reached.

2 Survey evidence

Before delving into the empirical methodologies, we provide an overview of banks' own cost of equity estimates and the methodologies that are employed to measure them. The ECB, in pursuing its banking supervision mandate, collects data on the cost of equity for significant euro area institutions on an annual basis. These data cover cost of equity estimates as assessed by the banks themselves, but also shed some light on the methodologies that institutions use for their estimations. Finally, the data contain qualitative information on the past and anticipated trends for the cost of equity for a three-year horizon. The survey covers 95 significant institutions based in the euro area, that together account for about 90% of the assets of the significant institutions as a whole.[1]

The weighted average of self-assessed cost of equity in Q4 2019 was 8.5%, while roughly two-thirds of the sample reported cost of equity of between 8% and 12% (Chart 1). Interestingly, almost 12% of the reporting significant institutions gave a cost of equity below 5%. On the other side of the spectrum, four banks report a cost of equity of more than 12%.

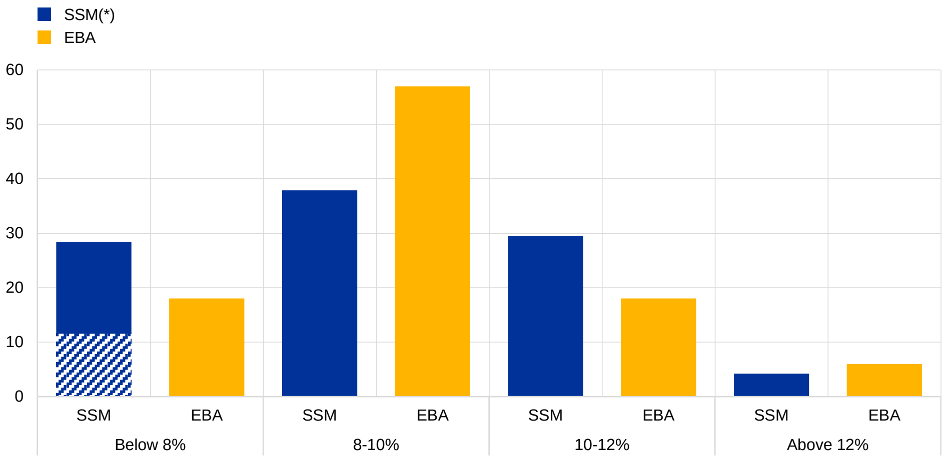
The Single Supervisory Mechanism (SSM) survey results are comparable to those reported by the European Banking Authority (EBA) for EU banks (Chart 1). The distribution of the cost of equity of SSM banks is somewhat more fat-tailed on the left-hand side than that of the EBA sample, with more banks reporting estimates below 8%. However, this is related to the differences in the composition of the two responding groups, as the EBA sample consists of fewer banks (65) while also covering non-SSM EU countries such as the UK.

1 Some banks consider cost of equity to be an irrelevant concept for them and, as a result, refrain from reporting it. Development/promotional lenders sometimes fall into this group of banks that do not use cost of equity as a benchmark for their returns.

Chart 1

Self-assessed cost of equity of European banks

(percentage; SSM data referring to Q4 2019; EBA data collected in autumn 2019)

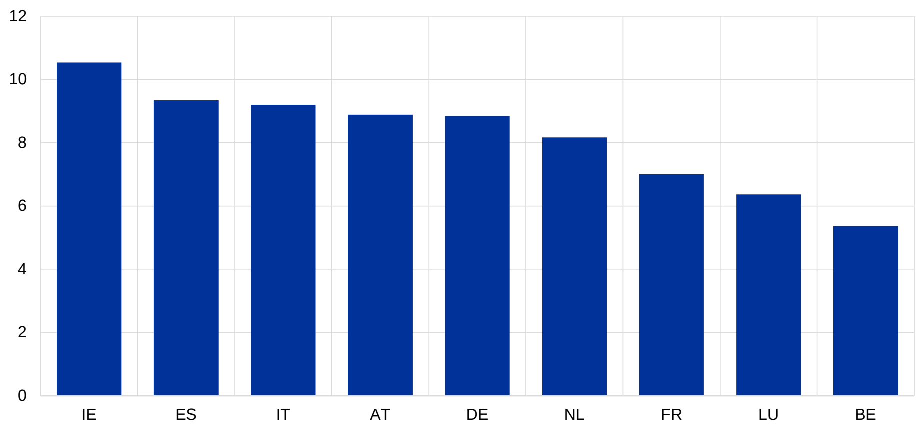


Sources: EBA, ECB, ECB calculations.
Notes: For the SSM, sample of 95 euro area significant institutions. The striped bar shows the share of SSM banks with COE below 5%. EBA data for 65 EU banks from the "Risk Assessment Questionnaire – Summary of the Results", Autumn 2019.

Chart 2

Self-assessed cost of equity of euro area significant institutions by home country

(percentage; data referring to Q4 2019)



Sources: ECB, ECB calculations.
Notes: Countries with less than four reporting banks are excluded. Country averages weighted by book value of equity.

Country and business model breakdowns show significant heterogeneity, while unlisted banks report lower cost of equity than listed banks. Banks in countries which were among those most affected by the euro area sovereign debt crisis report higher cost of equity than those in the less affected countries (Chart 2). In terms of business model, small market lenders, which are mainly active in central and eastern European countries and retail/consumer credit lenders report a cost of equity above 10%, and are followed by diversified lenders and global systemically important banks (G-SIB)/G-SIB universal institutions (Chart 3).[2] Development/promotional lenders

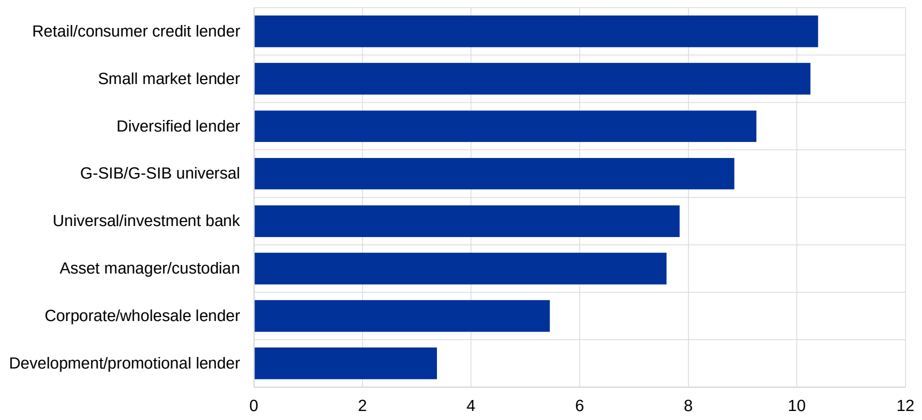
[2] We use the business model classification applied to SSM significant institutions in the ECB Supervisory Banking Statistics. See e.g. here.

report an average cost of equity around 3%, possibly because they tend to view themselves as institutions whose primary target is not profit maximisation. Finally, unlisted banks report a lower cost of equity than their listed peers (Chart 4).

Chart 3

Self-assessed cost of euro area significant institutions by business model

(percentage; data referring to Q4 2019)

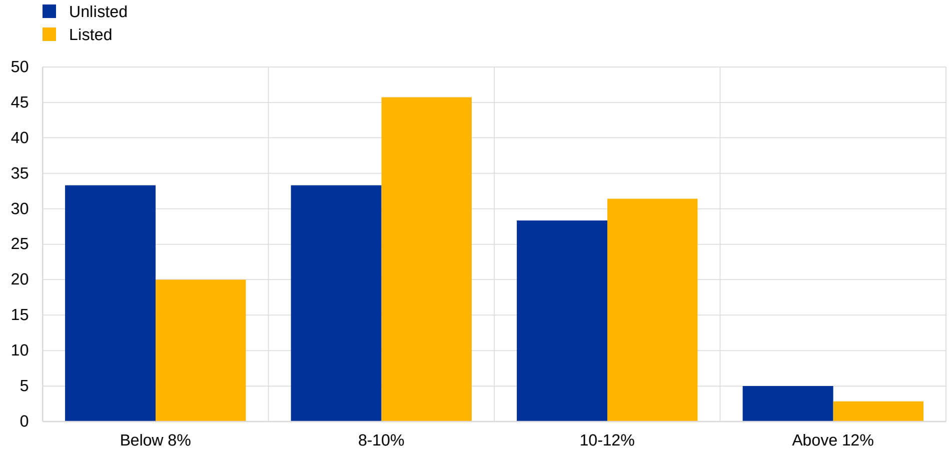


Sources: ECB, ECB calculations.
Note: Weighted by book value of equity.

Chart 4

Self-assessed cost of equity of listed vs unlisted euro area significant institutions

(percentage; data referring to Q4 2019)



Sources: ECB, ECB calculations.

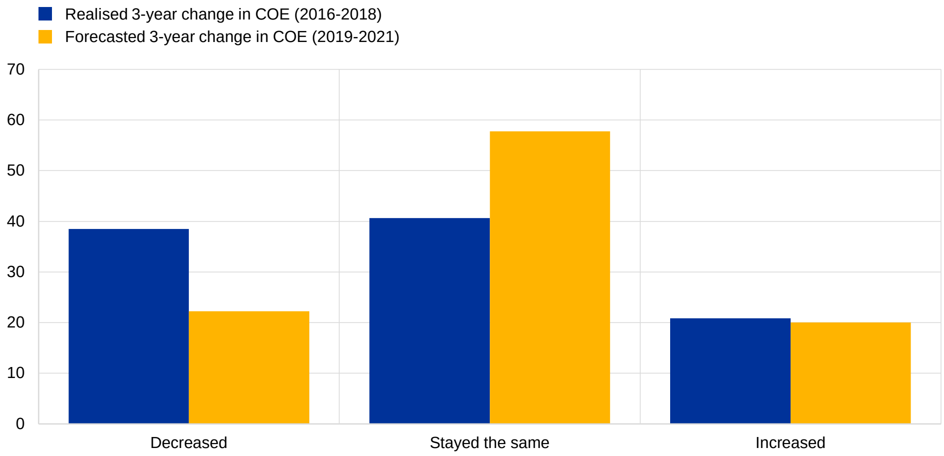
The majority of significant institutions reported that their cost of equity had decreased or stayed the same between 2017 and 2019, while the majority of banks expected the cost of equity to stay the same for the 2019-22 period (Chart 5). The forecasts of increased cost of equity may be outdated, as the banks reported the data before the outbreak of the COVID-19 crisis in Europe, which has led investors to re-evaluate risk premia in the context of an expected global recession. As growth expectations were revised downwards in the course of 2020 and uncertainty has increased, the estimated cost of equity estimates of the banks may well have been revised upwards since.

Significant institutions use different ways of estimating cost of equity (Chart 6). The largest group of respondents (41%) use some calibration of the standard Capital Asset Pricing Model (CAPM) and a further 9% use other model-based approaches, such as cash flow/dividend discount models. The model-based approaches are favoured by listed banks, which can make use of their stock price data to infer their required rate of return. Unlisted banks follow a more diverse set of methods, including qualitative approaches and discussions with stakeholders.[3] Finally, some banks also follow hybrid approaches (listed under "other") that combine internally maintained valuation models and markets analysts' input, apply the cost of equity of their peers or rely entirely on external consultants.

Chart 5

Realised and forecasted trend of cost of equity of euro area significant institutions

(percentage; data referring to Q4 2019)



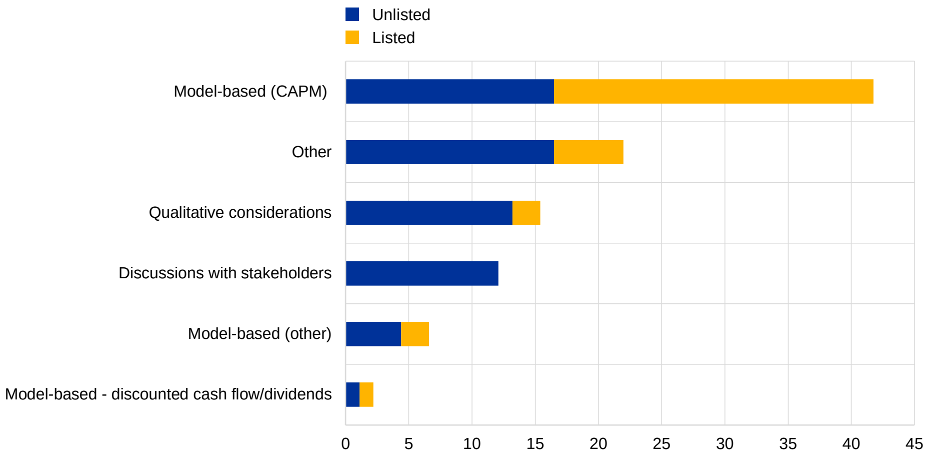
Source: ECB calculations based on qualitative questionnaire answers.

[3] Uses of CAPM by unlisted banks should not come as a surprise. Some of these banks reportedly make an assumption of their market beta based on their listed peers and calculate their cost of equity accordingly.

Chart 6

Reported estimation methods for cost of equity of euro area significant institutions

(percentage; data referring to Q4 2019)



Sources: ECB, ECB calculations.
Note: The sample contains 58 unlisted and 33 listed banks.

The use of self-reported cost of equity provides valuable insights in the required rate of return of the euro area banking sector but also has some potential biases. On the one hand, banks' self-assessment provides information that would be hard to obtain otherwise, especially in the case of entities that follow qualitative considerations, discussions with shareholders or hybrid approaches, i.e. cases where no single model has been applied. On the other hand, the possibility that banks provide estimates that are biased downwards cannot be excluded, given that their cost of equity can be benchmarked against their profitability to assess the sustainability of their business model.[4] Moreover, around one in three banks reported exactly the same cost of equity in 2018 and 2019, which may imply that certain banks do not update their estimates frequently enough.

[4] For such comparisons between profitability and cost of equity, see Profitability numbers are looking up, but not enough, SSM Supervision Newsletter, August 2019, and Profitability: banks expect to remain under pressure, SSM Supervision Newsletter, November 2019.

3 Empirical methodologies

This section presents the different methodologies that form our basis for measuring the cost of equity of euro area banks. More specifically, the section discusses the estimation step in our three-step methodology and summarises the results of ten different models grouped into two broad categories: factor models and implied cost of equity models.

In order to estimate the cost of equity of euro area banks, we rely on several publicly available databases.[5] We obtained data for bank stock prices, market capitalisation and book value of equity from Bloomberg. We obtained analyst forecasts of banks earnings, dividends and book value of equity using Refinitiv Eikon data. We restricted our sample to those banks for which we can obtain cost of equity estimates for the two broad sets of models described in the following chapters. We exclude banks with an average market capitalisation below €1 billion to account for possibly illiquid stocks. We also excluded banks whose free-floating shares account for less than 25% of their total shares to allow for government ownership and subsidiaries. This yields a sample of about 50 listed euro area banks for which we estimate the cost of equity. Our sample period starts in January 2004 and ends in December 2019.

3.1 Factor models

We estimate banks' cost of equity using five different models within the class of the multi-factor models developed in the asset pricing literature. At their core, these models follow the general paradigm of Markowitz' (1952) portfolio theory which states that in an efficient market place higher returns can only be accomplished by assuming greater risks. Most asset pricing models focus on systematic risk, i.e. risk factors that are common for a certain set of assets. The assets' risk exposures to these risk factors are typically referred to as betas or factor loadings and equate to the *amount* of risk with respect to each risk factor. Closely related is the concept of the risk premium, which represents the expected return of an asset with unique exposure to this risk factor, or the price of this risk. Both together form the cost of equity. The first model we use is the standard one-factor Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966) due to its simplicity and unabated popularity amongst practitioners and academics. We then extended the analysis by applying the Fama and French (1993) three-factor model to estimate the cost of equity[6] and a *multi*-factor model with credit variables which is grounded in the arbitrage pricing theory of Ross (1976). This model utilises factors from the literature on common risk drivers of bank's stock returns, capturing corporate and sovereign

[5] This paragraph highlights the bank and index specific data used for the estimation of cost of equity. For additional information about the data used for euro area-wide common factors applied in the factor model approach, see chapter A.2 of the Appendix.

[6] See Fama and French (1997) for an application of the CAPM and the Fama-French three-factor model to cost of equity estimation.

credit risk. For each multi-factor model, we included one additional specification with orthogonalised factors, for a total of five cost of equity estimates.

In this paper, we consider factor models with time varying beta coefficients and time invariant risk premia. In expected return-beta representation, the multi-factor asset pricing models we consider can be expressed as:

$$E(\tilde{R}_{i,t}) = \beta_{i,t}'\lambda$$

Where $\tilde{R}_t$ is the return (in excess of the risk-free rate) of asset i (which could be the stock of an individual firm or an equity index) and λ is the vector of risk premia associated with the model's risk factors. We used the one-year euro overnight index swap (OIS) rate to approximate the annual euro area risk-free interest rate, which we converted into a weekly return in order to compute excess returns.[7] The risk factor loadings are obtained from the following time series regressions:

$$\tilde{R}_{i,t} = \alpha_i + \beta_{i,t}' f_t + \varepsilon_{i,t}$$

where f_t is the vector of risk factors, while α_i is the regression constant, and $\varepsilon_{i,t}$ the regression residual. All our risk factors are traded returns and therefore the associated risk premia simply reduce to the expected values of these risk factors: $\lambda = E(f_t)$.

In the CAPM, only the excess return of the market portfolio is included as a single risk factor. The CAPM is widely used to estimate the cost of equity (see survey results in Section 3) but has important empirical shortcomings. Specifically, there is ample evidence that it fails to explain the cross-section of stock returns, see e.g. Fama and French (1992) and the references cited.

We also used the three-factor model of Fama and French (1993) which is, arguably, the industry standard in the realm of multi-factor models for stock returns. This model includes other factors in addition to the market factor and is able to better model stock returns. The Fama-French factors for size (small minus big – SMB) and value (high minus low – HML) are derived from dynamically sorting firms into portfolios according to their market capitalisation (size) and their ratio of book equity to market equity (value). SMB is the return difference of small and big firms, while HML is the return difference of firms with high and low book-to-market ratios. While the Fama-French HML and SMB factors are derived from a large sample of listed *non-financial firms*, the literature provides evidence that they have a strong explanatory power also for banks. Barber and Lyon (1987) document that the relationship between firm size and book-to-market ratios and stock returns is similar for financial and non-financial firms. Schuermann and Stiroh (2006) employ the Fama-French HML and SMB factors to model US bank stock returns and document their strong explanatory power in time series regressions. Adrian, Friedman and Muir (2015) include the Fama-French HML and SMB factors in a model for the COE of the US financial sector. In this paper, we apply the HML and SMB factors derived from a large sample of listed European firms, which we obtain directly from Kenneth French's

[7] Preferably, one would use an exactly maturity matched risk-free rate of return, i.e. the return of a risk-free asset with a maturity of exactly one week for our analysis of weekly returns. Due to data limitations and volatility issues for OIS rates with maturities shorter than one year, we opted for the one-year rate as a trade-off between precision, data availability and behaviour of the interest-rate time series.

data library.[8] The Fama-French factors are primarily empirically motivated. Therefore, an alternative is to employ factors that have a clear theoretical motivation as risk drivers for banks.

For the second multi-factor model, we added two factors, linked by the literature to banks' risk drivers, to the market factor: measuring corporate credit and sovereign risks. These factors directly reflect banks' business activities and inherent risk exposures. They are constructed from the returns of BBB-rated corporate bonds (BBB) and from sovereign bonds of lower-rated euro area Member States (SOV), respectively.[9] Bessler and Kurmann (2012) employ similar factors in their analysis and document their importance in explaining the returns of euro area bank stocks. The clear interpretability as risk factors for banks could make them preferable to decision makers when compared to the Fama-French factors.[10]

We orthogonalised the risk factors to eliminate correlations between them. Correlation with the market factor in particular could arise as the market factor summarises a large set of risks, possibly overlapping with other factors. The orthogonalisation is achieved by sequentially regressing factors onto each other and constructing the orthogonalised factor from the residual and constant. More specifically, for the Fama-French three-factor model, we first regressed the market factor on HML and SMB and then SMB on HML, while for the model with credit variables, we first regressed the market factor on BBB and SOV and then BBB on SOV[11]. In this paper, we estimate one additional specification of each multi-factor model using this orthogonalised series (for the estimation of betas as well as risk premia) for a total of five separate factor-model based COE estimates.

Banks' risk exposures can change over time. Here, we employ the Dynamic Conditional Beta approach of Engle (2016) to estimate time-varying betas. In this approach, time-varying beta coefficients are expressed as follows:

$$\beta_t = H_{ff,t}^{-1} H_{f\tilde{R},t}$$

where $H_{ff,t}^{-1}$ is the inverse of the variance-covariance matrix of f and $H_{f\tilde{R},t}$ the covariance of f and $\tilde{R}$, each at time t, which can be obtained by partitioning the joint time-varying variance-covariance matrix H_t. We estimate H_t using the dynamic conditional correlations (DCC) model of Engle (2002), which allows for beta estimates that react instantaneously to changing market conditions. This is a distinct advantage over rolling regressions, which assume constant betas within the estimation window

8 Fama-French factors from the data library of Kenneth French. See Fama and French (2012) for the construction of these factors and evidence about the Fama-French factors for international stock returns.

9 The appendix contains a detailed description of these factors.

10 Furthermore, because we obtained the Fama-French factors from the data library of Kenneth French, where they are being made available with some time lag, the model with credit variables has the advantage of being able to produce more timely estimates.

11 The ordering of factors in the orthogonalisation procedure was chosen so that the impacts of all remaining factors are removed from the market factor. It should be kept in mind that different orderings can result in different estimates.

and appear to provide estimates with a lag.[12] We compare the results from the DCC model to rolling window estimates in the robustness Section A.1 of the Appendix.

One key challenge in factor models is the estimation error for risk exposures. This is relevant given that inefficient or biased estimates will lead to imprecise cost of equity estimates. Incorporating cross-sectional information by transforming beta estimates using a version of the Vasicek (1973) Bayesian Shrinkage Factor can improve estimates. We shrink each time-series estimate towards the cross-sectional mean, $\beta_{i,t,k}^{shrinkage} = w_{i,k}\beta_{i,t,k} * (1 - w_{i,k})\bar{\beta}_k$, whereby k denotes the risk factor. The shrinkage weighting is bank and factor-specific but constant over time, and is given by the ratio of time-series and cross-sectional variance of betas: $w_{i,k} = 1 - \sigma_{i,k,ts}^2/(\sigma_{i,k,ts}^2 + \sigma_{k,xs}^2)$, i.e. the estimator places more weight on the time series estimate when its variance is small compared to the cross-sectional variance of betas.[13] The robustness section of the appendix compares results with and without the application of shrinkage.

3.2 Aggregate cost of equity based on factor models

To check the performance of factor models, we first estimated the cost of equity for portfolio indices before moving to estimates for individual banks in the next section. Factor asset pricing models are designed to capture systematic risk which is common across assets, as opposed to single-asset idiosyncratic risk which tends to be eliminated through diversification. This leads to parameters estimated from portfolios tending to be more stable compared to firm-level estimates, and to a higher explanatory power for the models. In this section, we present estimates for returns of portfolios obtained by dynamically sorting banks according to their size (market value of equity) and price-to-book (P/B) ratios, as well for the euro aggregate banking sector index. We estimate the cost of equity based on multi-factor models for the time period, starting with the failure of Lehman Brothers (15 September 2008), as market participants have significantly revised their risk perception of banks since the global financial crisis.[14]

Cost of equity varies distinctly across models and banks of different size and valuations. Chart 7 displays COE estimation results based on full-sample regressions the five factor model specifications. The distinction between larger and smaller, as well as higher valued and lower-valued banks, is visible for all models. While the CAPM produces the lowest COE estimates, the Fama-French model displays distinctly higher results, and the model with credit variables leads to

---

12 The Dynamic Conditional Correlations (DCC) model of Engle (2002) is a variation of multivariate generalised autoregressive conditional heteroskedasticity (GARCH) models, which has been developed specifically to estimate conditional covariance matrices of financial time series data and take into account common features of financial time series, such as heteroscedasticity, volatility clustering, and serial correlation. Bali and Engle (2010) use the DCC model to estimate time-varying CAPM betas, while Engle (2016) employs the DCC model to estimate multi-factor asset pricing model betas, specifically the Fama-French three factor model.

13 See Vasicek (1973), Frazzini and Pedersen (2014) and Levi and Welch (2015) for additional motivation and details.

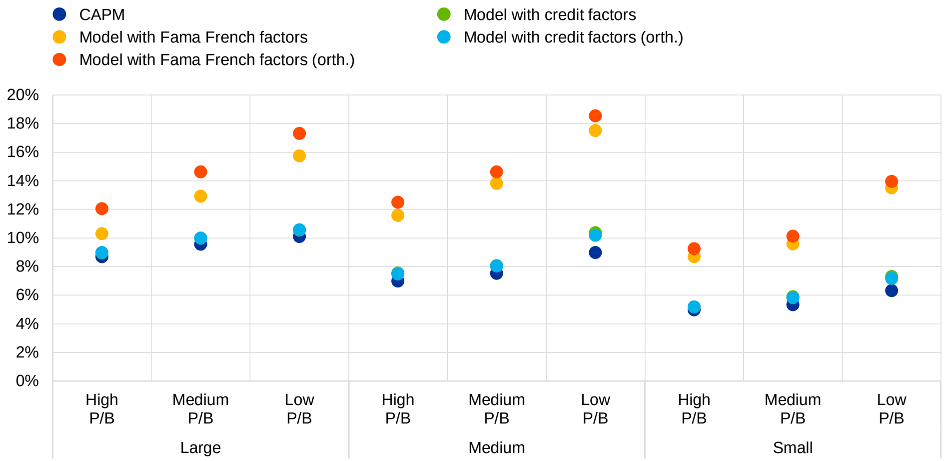
14 This is reflected in a distinct change in the level and significance of beta estimates that can be found when comparing pre and post-crisis regressions, in particular for the corporate and sovereign credit factors.

estimates between the two other models. In addition, a decomposition of the cost of equity into its components can highlight the relative importance of each risk factor. Chart A.3 in the annex shows a decomposition of the static COE estimates into their contributing components (i.e. the products of beta coefficients with the respective risk premia in addition to the risk-free rate). This decomposition highlights the importance of the HML factor, which adds distinctly to the final COE estimate in the Fama-French model, in particular in the orthogonalised specification. The HML component is generally more important for banks with lower price-to-book (P/B) ratios, which is in line with economic intuition and indicates that euro area banks' COE is related to their valuations. Annex A.2 contains a detailed description of our bank sample and how we perform portfolio sorts, while Annex A.3 contains additional estimation results, including for banking sector indices at country level.

Chart 7

Cost of equity for the euro area banking sector based on factor models

(percent)



Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This chart contains COE estimates based on full-sample time series regressions (i.e. static betas) of portfolio indices for banks on risk factors. Portfolios are obtained by dynamically sorting banks according to their size (market value of equity) and then conditionally on their P/B ratio (see Section A.2 in the appendix for details). Regressions are based on weekly data from 18/09/2009 to 27/12/2019. For corresponding risk premium and beta estimates, see Section A.2 in the appendix.

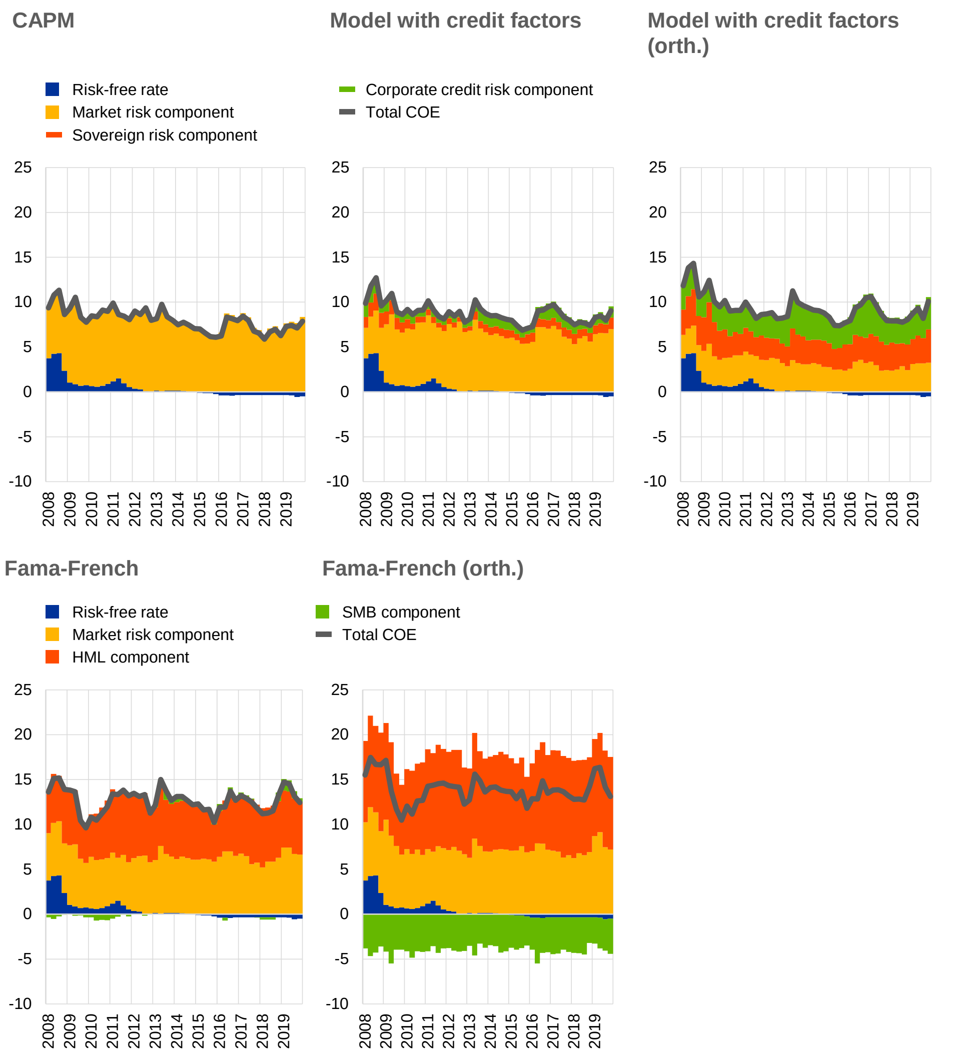
Compared to 2008, the mechanical impact of reductions of the risk-free rate on the COE estimates has been largely offset by significant increases in the risk components. Chart 8 displays the cost of equity estimated for the aggregate euro area banking sector index over time, decomposed into its components for the five models, including the orthogonalised specifications.[15] While risk-free rates are not included directly in the COE models as a risk factor, the models use excess returns computed on top of the risk-free rate. As short-term interest rates moved into negative territory, this mechanically put downward pressure on the cost of equity, while increased exposure to risk pulled the cost of risk in the opposite direction. In the case of the CAPM, the risk-free rate accounted for around 40% of the total COE in 2008,

[15] The orthogonalisation of the factors allows for a clearer representation of each factor's importance for the COE and more precisely reflects the risk it is meant to capture. As the general market risk factor reflects an aggregated assessment of all available information at a given time, it likely to also contain information which is already captured by the remaining factors. The same is also true for the other risk factors with respect to each other. The orthogonalisation procedure removes any such possible information overlap between the factors.

while it now negatively contributes to its level. In particular, the model with orthogonalised credit variables shows variation in the importance of the market, credit and sovereign risk factors over time. During the global financial crisis, both the sovereign and market risk factors contributed to the higher cost of equity. This was followed by an increase in the sovereign risk factor following the euro area debt crisis. The credit risk factor has gained particular importance in the wake of the euro area debt crisis. The Fama-French three factor model shows the clear importance of the value factor (HML) for the euro area banking sector, which has struggled with low valuations since the global financial crisis. The contribution of this factor has increased during and following the euro area debt crisis and has gained in prominence again more recently, pushing the estimated COE briefly above 15% at the end of 2018.

Chart 8

Time-varying cost of equity for the euro area banking sector based on factor models



Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: The chart contains COE estimates based on time-varying betas (DCC model) and five different factor model specifications for the euro area aggregate banking sector index. Estimations are based on weekly data from 21 September 2007 to 27 December 2019, with the first year of data being used as a burn-in period. The chart shows quarterly averages from Q1 2008 until Q4 2019. For the corresponding risk premia estimates, see Section A.3 in the appendix. The second and fourth panels show results from models with orthogonalised factors (see appendix A.2 for details about the orthogonalisation procedure).

3.3 The implied cost of equity models

An alternative way to estimate the cost of equity is the implied cost of capital approach, which relies on expectations of banks' future earnings and growth. This approach was developed partly in response to some limitations in inferring equity premia from observed returns. In contrast to the models discussed in Section 3.1, which extrapolate the cost of equity using historical data of market prices, the implied cost of capital approach also incorporates forward-looking information, such as accounting information on expected future dividends or cash flows.

The implied cost of capital approach relies on some version of the discounted cash flow model. The discounted cash flow model sets the stock price as equal to the discounted value of all expected future cash flows. Mathematically, this is expressed as

$$P_0 = \sum_{t=1}^{\infty} \frac{CF_t}{(1+r)^t} \tag{1}$$

where P_0 is the current stock price, CF_t is expected future cash flows in period t, and r is the discount rate, that is, the cost of equity. The general intuition underlying this model is that shares represent a claim on future earnings streams. Given that market prices and expectations of future cash flows are observable, it is possible to back out the cost of equity by identifying the discount rate r, that equates the current market value per share of a particular bank's equity P_0 to the present value of its forecasted future cash flows CF_t.

We estimate the implied cost of equity using five empirical models that are well-established in the literature. Our first model is based on Damodaran (2017) and is a discount model using a free cash flow to equity proxy. The second model uses the abnormal growth in earnings model by Ohlson and Juettner-Nauroth (OJS) (2005). The third model is a simplified version of this model. We then provide two models based on the residual income model: Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001). We explain all the models in detail in technical appendix A2. These methodologies differ mainly in their assumptions of future cash flow patterns and on the accounting measures that analysts forecast.

The abnormal growth in earnings models links market price to capitalised future earnings and adjusts this value using future expected abnormal growth in earnings. There are two main variations of this model in the literature that are used to estimate the cost of equity capital. The first is the original model of Ohlson and Juettner-Nauroth (2005), which relates the firm's price per share to next year's expected earnings per share (EPS) and to both short-term and long-term growth in EPS. With these elements in place, it is then possible to back out the cost of equity by expressing it as a function of the forward EPS to price ratio and the two measures of growth in expected EPS. The simplified version assumes a constant long-term growth and ignores dividends, as in Easton (2004), Gode and Mohanram (2013) and Dick-Nielsen et al. (2019).

The residual income valuation model values a company not only based on discounted future earnings but also on the book value of the company's equity. The residual income model is a reformulation of the dividend discount model using accounting variables. Instead of using projected dividends, the residual income model implicitly backs them out from the relationship that dividends equal earnings less changes in accounting (or book) values of equity, as shown in the equation below:

$$D_t = E_t - (BV_t - BV_{t-1}) \quad (2)$$

where D_t is current dividends, E_t is current earnings and $(BV_t - BV_{t-1})$ is the difference between current book value and previous book value of equity. While the abnormal growth model of Ohlson and Juettner-Nauroth links market price to capitalised future earnings and adjusts this value through future expected abnormal growth in earnings, the residual income model adjusts this valuation through future expected residual income.[16]

We collected analyst consensus forecasts using the Institutional Brokers' Estimate System (I/B/E/S) (Refinitiv Eikon) data available from the beginning of 2005. For European firms, I/B/E/S provides measures up to 4 years ahead. For European firms, there are no five-year ahead earnings' forecasts, while the three and four-year forecasts can be extremely sparse. On dates when earnings' forecasts are not available, we replaced them with the most recent realised growth rate in earnings for that bank. If recent realised earnings were missing, we input the median growth in earnings' forecasts over euro area banks belonging to the same market capitalisation group as the bank in question, where the median was computed for the missing month.

A key assumption in our analysis is how we estimated the short-term and long-term growth rates of future earnings. To be consistent across models, we used the same estimation for all models. The long-term growth rate (g^L) is set as being equal to the five-year ahead International Monetary Fund (IMF) forecast for annual real GDP growth for the euro area. Our proxy for g^L is different from the literature applying this method to US firms (see Gode and Mohanram, 2003, 2013, Dick-Nielsen et al., 2019), where g^L is equal to the 10-year US Treasury bond yield minus 3%. We opted not to use a 10-year OIS rate, as it has become negative in more recent periods. Moreover, it is reasonable that investors expect a long-term growth rate matching the growth rate for the rest of the euro area economy. The short-term growth rate (g_S) was computed for EPS as a geometric average of year-on-year growth rates: $g^S = \left(\frac{EPS_K}{EPS_1}\right)^{\frac{1}{K-1}} - 1$, where K=4. Where the year-end earnings forecasts were not available, the most recent available forecasts were used.[17]

---

16 One potential limitation of using clean surplus accounting is that it does not account for changes in equity due to other comprehensive income (OCI). This may be particularly relevant for changes in the equity of banks given that a significant share of their government debt securities is classified as OCI.

17 This approach is also different from applications to US firms, which employ a geometric average of the forecast growth rate from year 1 to year 2 and the forecast growth rate from year 1 to year 5 (see e.g. Gode and Mohanram, 2003, 2013, and Dick-Nielsen et al, 2019).

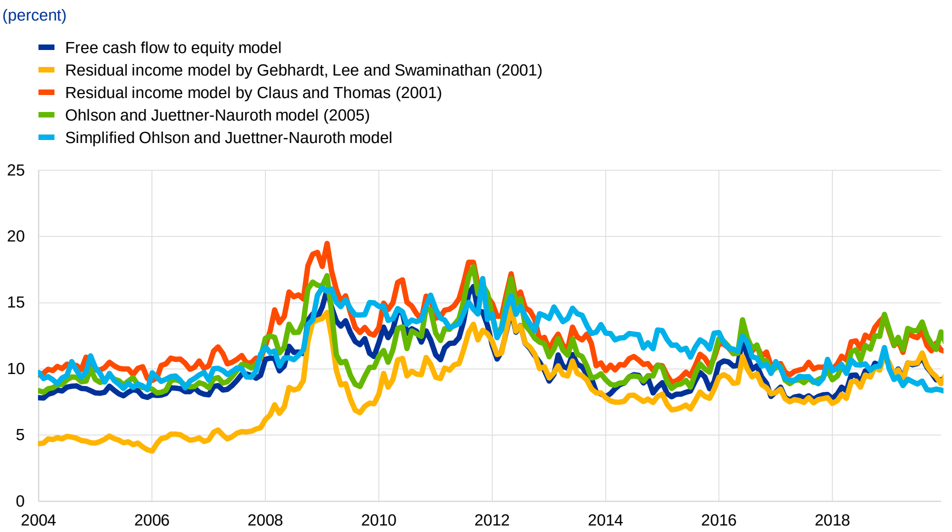
Another important assumption is that the forecasts of future earnings are consistent with investor expectations as reflected in stock prices. There has been a lively discussion about the extent to which analyst forecasts are biased, and several papers have found that, in the United States, these forecasts tend to be overly optimistic ex post as compared to realised returns. If analyst forecasts are overly optimistic and market prices do not also reflect this optimism, then there will be an upward bias in the cost of equity. So (2013) found that investors tended to overweigh the influence of analyst forecasts in their investment decisions, meaning that if bias exists in analyst forecasts, it will also be likely to exist in market prices. Based on this, we do not consider it appropriate to adjust for optimism in the analyst forecasts.

3.4 Results from implied cost of equity models

There is considerable variation in the estimates of the cost of equity using the five implied cost of capital models (Chart 9). Over the full sample, most models lie within a relatively narrow range of each other. One exception is the model of Gebhardt, Lee, and Swaminathan (GLS), which typically yields the lowest estimate, with an average estimate of 8.8%. This was especially the case before the 2008 crisis, when its estimates were persistently lower than the other models by a large degree. The four other models were quite close to each other, with average cost of equity estimates within a range of between 9.8% and 12.7%.

Chart 9

Cost of equity estimates for the euro area using the implied cost of equity capital method



Sources: Bloomberg, Refinitiv, and ECB calculations.
Note: Latest observation: December 2019.

All five implied cost of capital models increase and move closely together in periods of extreme financial stress. The covariance between these models is typically quite strong, but this is particularly visible in crisis periods, when the estimates of all five models increase significantly. There are two potential ways of interpreting this result. The first case is when analyst earnings expectations and the model assumptions around the future growth rate of earnings are consistent with those of investors. Where this is the case, our estimates are non-biased and reflect an increase in investors' discount rate of future earnings. The second case is when the expected future earnings implied from our models are higher than investors' expectations. This may be due to either analyst optimism in their forecasts or uncertainty around the model assumptions on the future growth rate of earnings. If investor' actual earnings expectations are below those in our model, then our cost of equity estimates will not fully reflect changes in investors' discount rate and therefore will include an upward bias. As discussed in the previous section, on average we should expect that analyst and investor expectations are broadly aligned.

4 Results and model averaging estimates

4.1 Comparison among models

The completion of the first step (model estimation) of our three-step methodology shows considerable heterogeneity across our ten models (Table 1). There is quite a wide range in median estimates for our ten models, which range from 7.1% for the CAPM to 12.1% for the Fama-French three-factor model. Regarding the percentiles, the GLS model produces the lowest estimate at the 10th percentile, while the OJS model produces the highest estimate at the 90th percentile.

While there is considerable heterogeneity across the ten individual models, there does not appear to be any systematic upward or downward bias in our estimates. In particular, no clear persistent bias is visible between the two sets of models.

Table 1

Summary statistics for cost of equity estimates for euro area banks using ten models

(percent)

	CAPM	FF	FF o.	Credit	Credit o.	FCFE	OJ	OJS	GLS	CT
Cross-section										
Mean	7.33	12.45	11.82	8.02	8.72	9.8	10.82	12.7	8.84	12.02
Median	7.16	12.1	11.43	7.84	8.52	9.07	10.09	11.44	7.83	11.11
SD	1.81	3.2	3.19	2.02	2.11	3.68	4.05	5.33	4.74	4.38
P10	5.29	8.84	8.29	5.8	6.44	6.1	6.54	6.9	3.75	7.67
P90	9.6	16.42	15.83	10.42	11.23	14.5	15.94	20.59	14.95	17.47
Time series										
Mean	7.32	12.44	11.81	8.02	8.72	9.72	10.66	12.59	8.44	11.93
Median	7.36	12.51	11.82	8.12	8.74	9.18	10.18	12.26	8.67	11.24
SD	0.95	1.22	1.26	0.91	1.01	1.96	2.32	2.35	2.97	2.48
P10	5.89	10.85	10.2	6.85	7.5	7.83	8.13	9.71	4.57	9.36
P90	8.53	13.98	13.37	9.21	10.04	12.55	13.77	15.92	12.15	15.7

Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This table shows summary statistics for our ten models. The cross-section panel reports summary statistics where the unit of observation is at the bank-model-time level. The time-series panel reports summary statistics where the unit of observation is the euro area weighted mean of each model, weighted by market capitalisation. Models 1-5 are the five factor models. CAPM is the CAPM model. FF is the standard Fama French three-factor model. FF o. is the Fama French three-factor model with orthogonalised factors. Credit is the three-factor model with credit factors. Credit o. is the orthogonalised version. Models 6-10 are the five implied cost of capital models. FCFE is free cash flow to equity model. OJ is the first of the abnormal growth in earnings models by Ohlson and Juettner-Nauroth (2005). OJS is the simplified version of the OJ model. GLS is the residual income model by Gebhardt, Lee, and Swaminathan (2001). CT is the residual income model by Claus and Thomas (2001).

4.2 Cost of equity estimates based on a model averaging approach

The absence of systematic upward or downward differences across models motivates the second step (model combination) of our three-step methodology.

Determining which model provides the most accurate estimate of the cost of equity faces several challenges. First, all models are simplifications of how investors demand compensation for the risk of holding banks' equity, and are therefore mis-specified to some extent. The considerable dispersion in estimates around periods of high uncertainty highlights this. Second, all models use different assumptions and information, which means that any individual model may include information that the others lack. The suitability of the information used in each model is likely to vary across time and across banks. Third, we are interested in obtaining bank level estimates, which means the issue of model uncertainty is even larger than it would be if we relied only on aggregate estimates. Fourth, since the cost of equity is not directly observable, there is no robust benchmark to assess the plausibility of our results. Considering that each model may be less biased than other models for some banks and during certain market conditions, there does not appear to be a reliable method for deciding which model is best.

The practice of averaging across different model estimations is common in both academic and industry practice. Empirical evidence in the forecasting literature shows that averaging results across models leads to more accurate results than relying on individual forecasts (see Clemen, 1989; Armstrong, 2001, and Timmermann, 2006). Besides the challenges of finding a consensus on which model works best, given their different advantages and deficiencies, the rationale behind averaging models is that it should reduce the idiosyncratic measurement error across them. The model averaging approach is also widely used in the implied cost of capital literature.[18]

Given the differences in information used, we consider that it is advisable to average over several models rather than prioritising any single model. Our combined method helps to minimise large errors when particular information or assumptions are not reliable in certain market situations. We therefore follow the approach of Green, Lopez and Wang (2003), who provide a methodology for estimating the cost of equity as part of the Federal Reserve's benchmarking exercise for the banks for which it provides its services. They argue that using a combined approach is a costless way of combining overlapping information sets on an ex post basis.[19]

The model-average cost of equity estimate for euro area banks is based on a three-step methodology. We first estimate for each bank individual estimates for the ten models that we use to estimate the cost of equity. We then combine the ten model estimates for each bank by averaging these estimates to arrive at a bank-level cost of equity estimate. Given that we do not have a credible way to rank the estimates in terms of their suitability, we take a simple average. Finally, we aggregate these estimates by value-weighting them according to a bank's market capitalisation for i) the euro area, ii) the four largest countries, and iii) business model classifications.

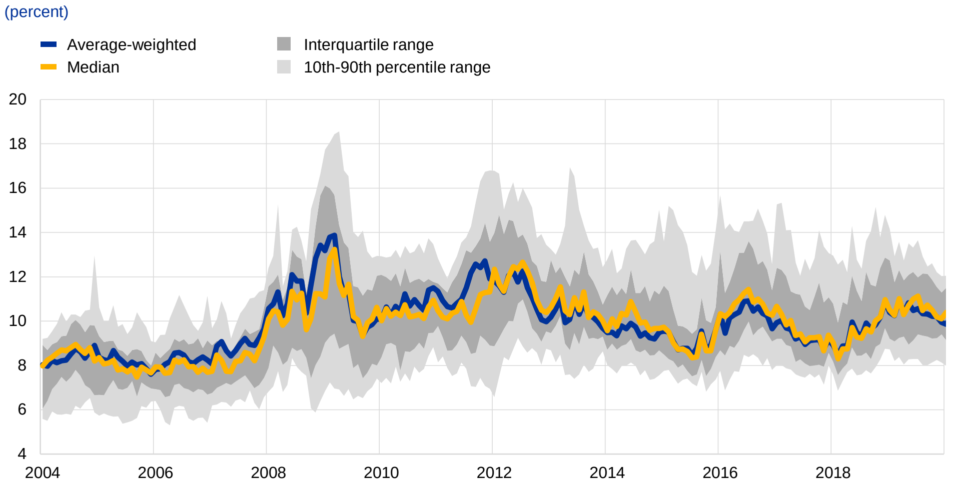
[18] See for example, Hail and Leuz (2006, 2009), Dhaliwal, Krull, and Li (2007), Boubakri, Guedhami and Mishra (2010), Chen, Chen and Wei (2011), El Ghoul, Guedhami, Kowk and Mishra (2011), Boubakri, Guedhami, Mishra and Saffar (2012), Gode and Mohanram (2013), and Dick-Nielsen et al (2019).

[19] In an earlier short contribution, European Central Bank (2015, 2016) propose imputing the equity risk premium for the whole equity market via a dividend discount model and then projecting this onto individual banks via their respective CAPM beta to yield bank-specific cost of equity.

The model-average cost of equity estimate shows considerable dispersion across euro area banks (Chart 10). While the central tendency of the cost of equity measure is not very sensitive as to whether we consider the median estimate or our preferred approach of taking the weighted-average across banks using market capitalisation, there is considerable heterogeneity over time across banks. At the end of 2019, the cost of equity ranged from 9.2% at the 10th percentile to 15.7% at the 90th percentile.

Chart 10

Cost of equity estimates for euro area banks using the model averaging approach

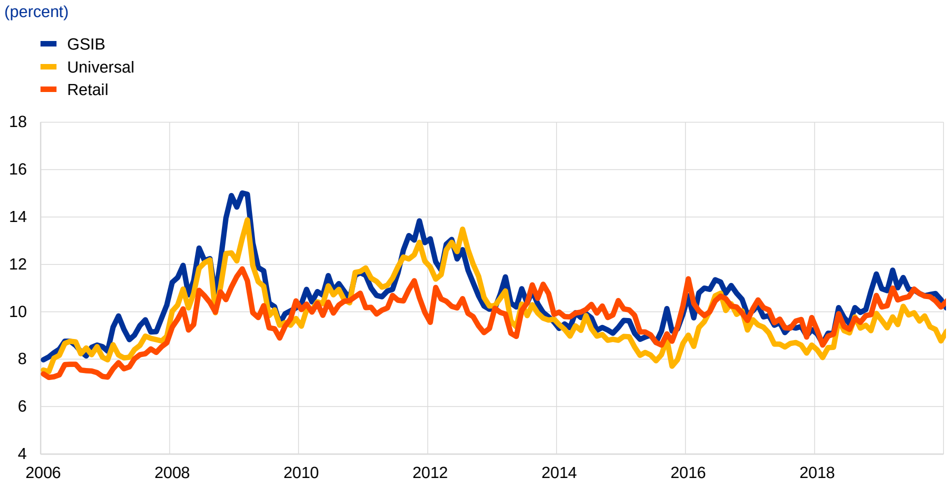


Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This chart shows the time-series of the model average estimates. EA is the euro area weighted average of the bank-level model average estimates, weighted by market capitalisation. The grey shaded area is the range between the 10th and 90th percentile of these estimates. Latest observation: December 2019.

The cost of equity is also heterogeneous across banks' business models (Chart 11). Given that banks have various activities operating in different lines of business and that these lines of business assume different types of risks, we may expect to see differences in banks' cost of equity across business models. We find that the cost of equity is highest for G-SIBs. While this is the inverse of the ranking obtained for banks' credit risk premia, it is consistent with banks' price-to-book ratios. This may reflect investor concerns around the complexity involved in managing G-SIB banks, and to a lesser extent universal banks, where various asset and liability instruments are particularly sensitive to changes in market valuations. Moreover, stricter regulations that specifically target G-SIBs, in addition to uncertainty around their implementation, may also dampen investor confidence. It is also worth noting that specific business models are more dominant in certain countries, and some of the dynamics may reflect country macroeconomic developments.

Chart 11

Cost of equity estimates for banks by business model classification



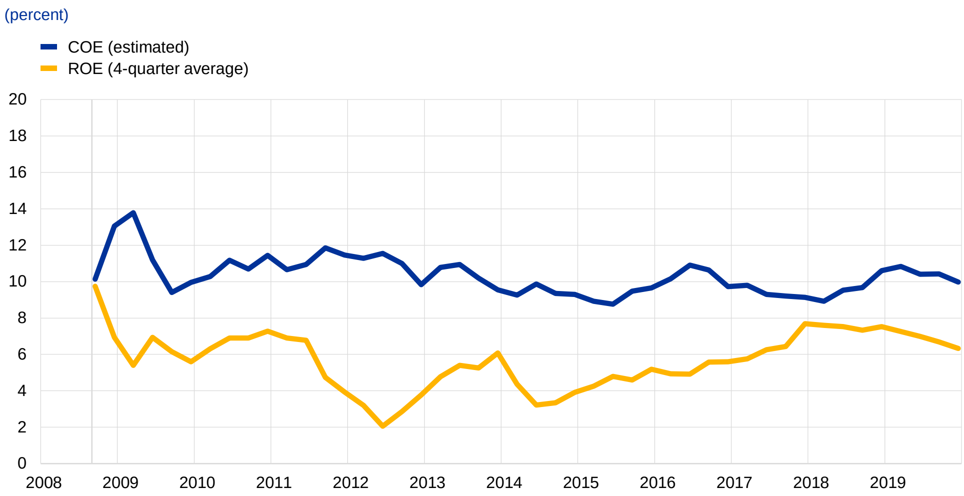
Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This chart shows the time-series of the model average estimate using four business model classifications. All estimates are a weighted average of the bank-level model average estimates, weighted by market capitalisation. The sample is composed of 8 G-SIBS, 6 universal banks and 23 retail lenders. Retail lenders combine banks belonging to the categories "retail and consumer lenders" and "diversified lenders". Latest observation: December 2019.

Banks' cost of equity has been consistently higher than banks' return on equity since the onset of the global financial crisis (Chart 12). The difference between the two metrics is widely used to assess whether banks' performance is aligned with investors' required return. Under certain conditions (such as when investors expect zero growth in bank dividends), the ROE-COE gap can coincide with banks' price-to-book ratio. Therefore, the fact that banks' COE has consistently and significantly exceeded their ROE may explain why the price-to-book ratios of major banks have fallen over the past decade to the extent that the market value of banks' equity trades at a significant discount to the book value of their equity.[20]

[20] For a discussion of euro area banks' profitability challenges see, Rostagno et al. (2019), Altavilla, Boucinha, Peydró (2018) and Andersson, Kok, Mirza, Móré and Mosthaf (2018).

Chart 12

Comparing banks' cost of equity and ROE



Sources: Bloomberg, Refinitiv, Kenneth French's data library, S&P Market Intelligence and ECB calculations.
Notes: This chart shows the time-series of the cost of equity and return on equity (ROE). Latest observation: December 2019.

4.3 Estimated cost of equity and bank fundamentals

In terms of the risk-return trade-offs that underlie financial decisions, cost of equity gauges investors' required rate of return and, simultaneously, the related level of risk that investors assume. Each bank has its own capital structure and liquidity management, operates at a certain level of cost efficiency and has to deal with its own more or less important legacy issues. Moreover, banks' equity risk is influenced by broad market movements and by the salient features of the underlying institutional framework, which is often determined at the jurisdiction level. All these factors influence the risk perceptions of investors and are therefore related to banks' cost of equity.

We assessed the plausibility of our cost of equity estimates at the granular level, making use of the economic fundamentals of banks discussed above. We ran regressions of quarterly bank-level cost of equity estimates on bank-level characteristics: (i) CET1 ratio as a proxy for leverage, (ii) interbank deposits over total assets as an indicator of reliance on unstable funding, (iii) the non-performing loan (NPL) ratio as a proxy for realised credit risk, and (iv) the cost-to-income ratio to capture operational efficiency. Moreover, we controlled for bank size and used country dummies and time dummies to capture time-invariant effects and the broad time-dependent evolution of cost of equity.

Our estimates of cost of equity have a plausible relationship with banks' fundamentals (Table 2). We ran five specifications to avoid our results being driven by a single model and used an unbalanced panel dataset of 44 listed banks for which we have quarterly data for the period Q4 2008 to Q4 2019. Two of the regressions are pooled ordinary least squares (OLS) and two are panel regressions with random effects (RE), each with and without country dummies. We finally ran a panel regression with bank fixed effects (FE), for which country dummies are, by construction, redundant. Banks with higher NPL ratios tend to have a higher cost of equity, given that their credit risk is elevated compared to peers. Similarly, banks that rely more strongly on other banks' deposits, which are a less stable source of funding than deposits from households and non-financial corporations, also tend to face a higher cost of equity. Also, banks with a higher cost-to-income ratio have a higher cost of equity, as their lower cost efficiency may be associated with a higher risk to shareholders. The estimates on NPLs ratio, interbank deposits and costs are similar to those of Goel et al. (2019), Bogdanova et al. (2018) and Grodzicki et al. (2019). The first paper reports similar relationships between bank fundamentals and bank probabilities of default (PDs) for a broader sample, while the other two uncover matching associations between bank fundamentals and valuations. Banks with higher CET1 ratio face lower cost of equity, in line with Dick-Nielsen et al. (2019) and European Central Bank (2011), although the result loses significance after bank-specific effects are accounted for.

Table 2

Cost of equity and bank fundamentals

(percent)

	(1) OLS	(2) OLS	(3) RE	(4) RE	(5) FE
CET1 ratio	-0.090*** (0.023)	-0.123*** (0.026)	-0.052 (0.037)	-0.050 (0.038)	-0.026 (0.038)
NPL ratio	0.092*** (0.005)	0.078*** (0.008)	0.067*** (0.014)	0.053*** (0.015)	0.047*** (0.015)
Interbank deposit ratio	0.070*** (0.008)	0.057*** (0.008)	0.065*** (0.015)	0.058*** (0.015)	0.054*** (0.016)
Cost-to-income ratio	0.035*** (0.006)	0.026*** (0.007)	0.022*** (0.006)	0.020*** (0.007)	0.016** (0.008)
Log (assets)	0.003*** (0.000)	0.003*** (0.001)	0.004*** (0.001)	0.005*** (0.002)	0.008 (0.006)
Country fixed effects	NO	YES	NO	YES	NO
Bank fixed effects	NO	NO	NO	NO	YES
Time fixed effects	YES	YES	YES	YES	YES
Obs.	1113	1113	1113	1113	1113
Adjusted R-squared	0.467	0.512	-	-	0.182
Overall R-squared	-	-	0.474	0.514	0.290

Sources: S&P Market Intelligence, ECB and ECB calculations.
Notes: RE and FE specifications clustered at the bank level. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

On a final note, larger banks tend to face a higher cost of equity in our estimations. This finding goes against the too-big-to-fail paradigm, whereby large banks benefit from implicit state guarantees. Among others, Gandhi and Lustig (2015) report such findings for the US, while Berndt et al. (2019) find that the probability of state support of G-SIBs has decreased in recent times. Goel et al. (2019) similarly report the decrease in importance of G-SIBs. Such findings point to a negative or flat relationship between size and bank cost of equity. That said, our sample focused on euro area banks in the post-financial crisis period, which was characterised by increased sensitivity to the bank-sovereign nexus (see e.g. Acharya et al., 2014), with some authors referring to some banks as “too-big-to-save” rather than too-big-to-fail (Demirgüç-Kunt and Huizinga, 2013). Moreover, bank size may act as a proxy for complexity, and there is evidence of diseconomies of scale which appear once banks go above a certain size (e.g. see Huljak et al., 2019, Andreeva et al., 2019, and the literature cited by them). Disentangling the various mechanisms that lie behind the positive relationship between size and COE is an interesting question per se but lies beyond the scope of this paper.

5 Cost of equity for unlisted banks

5.1 Motivation

This section extends the estimation methodology of Section 3 to also include unlisted euro area banks. The estimation methods described in Section 3 calculate euro area banks' cost of equity relying on, among other things, their stock market prices, making them suitable for listed banks only. Listed banks hold around two-thirds of total bank assets of significant institutions in the euro area. Still, the majority of significant banks (and most of the less significant ones) are not listed on a stock market, but are rather held privately or by public entities. This group also includes subsidiaries of non-euro area banking groups operating in the euro area.

Cost of equity can also be an important concept for unlisted banks, though not for all of them. Even without a link to stock market movements, cost of equity can have implications for unlisted banks – for instance in loan pricing decisions or questions of company valuation. Indeed, as discussed in Section 2, many of the unlisted significant institutions report their self-assessed cost of equity, which reflects the rate of return their owners expect them to achieve. It may be less relevant for some unlisted institutions, in particular when profit maximisation is of secondary importance, e.g. as is the case for publicly owned development banks mandated to extend credit to strategically important sectors.

The literature suggests that, in general, unlisted stocks may have a higher cost of equity than their listed peers due to illiquidity and, in some cases, the lack of diversification of owners. Kartashova (2014) finds that owners of unlisted equity (of all sectors, not only banks) have earned a higher return than owners of listed shares. The author puts forward the idea that unlisted equity carries an illiquidity premium that may explain the difference. Abudi et al. (2016) present a model that generates higher cost of equity for private firms through the channel of non-diversification of the owners, who hold the majority of their wealth in the equity of one company (see Moskowitz and Vissing-Jørgensen, 2002, for empirical evidence of this point) and therefore require higher earnings to compensate them for their concentration risk.

When focusing on euro area banks, it is not clear whether the cost of equity of unlisted institutions should be systematically higher or lower than that of listed banks. Importantly, unlisted banks are not necessarily held by private investors. In the euro area, governments, either central or local, are often key owners of unlisted banks (Véron, 2017). Given the size of the governments' budget and assets, it is hard to argue that such positions in bank shares are undiversified. More fundamentally, some of the state-owned banks have a mandate that goes beyond profit maximisation and may lead to them having lower or no required rate of return (see Section 2). On the other hand, some governments have gained holdings in banks with important legacy problems (such as high non-performing exposures), but have the intention of winding those positions down at a later point in time. We would expect these banks to have a cost of equity that is higher compared to healthier peers. Other investors in unlisted banks include foreign banking groups and financial investors, such as private equity funds, which are also likely holding diversified investment portfolios.

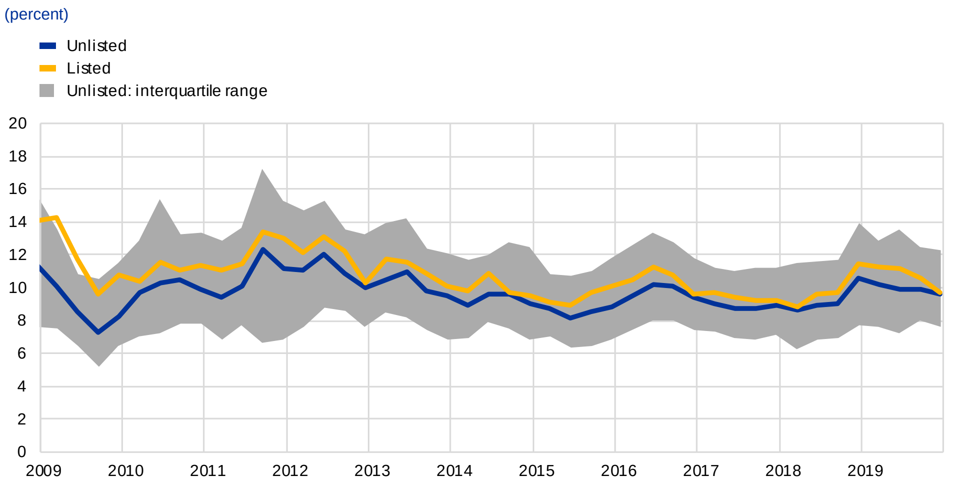
5.2 Methodology

We estimate what the cost of equity of unlisted banks would be if they were listed, making use of the measure's estimated relationship with bank-level fundamentals, extending the approach presented in Section 4.3.

Our methodology comprises of four steps. First, for each of the ten listed banks' specifications (see Section 2), we regress the model-specific cost of equity on bank-level characteristics. The relationships are similar to those we find for the average cost of equity in Section 4.3 (see appendix A.5 for the regressions' output). Second, we project the model-specific cost of equity values for unlisted banks, using their bank-level characteristics and the sensitivities of the regressions described in the previous step. The underlying assumption is that the regression coefficients are the same for unlisted banks as they were for the listed banks. This is another way of saying that we estimate the cost of equity of unlisted banks assuming that they were listed. Third, in order to take into account the model uncertainty that is inherent in the sensitivities of the regressions, we apply a multiple imputation method (Rubin, 1987) that generates five fitted values per bank and quarter, instead of the usual fitting with one value. This means that for any bank and quarter, we generate a range of cost of equity estimates, not a point estimate only. Finally, these estimates are then combined and aggregated in a similar way as the estimates of listed banks to generate bank-level cost of equity and broader aggregates.

Chart 13

Cost of equity estimates for listed and unlisted euro area banks



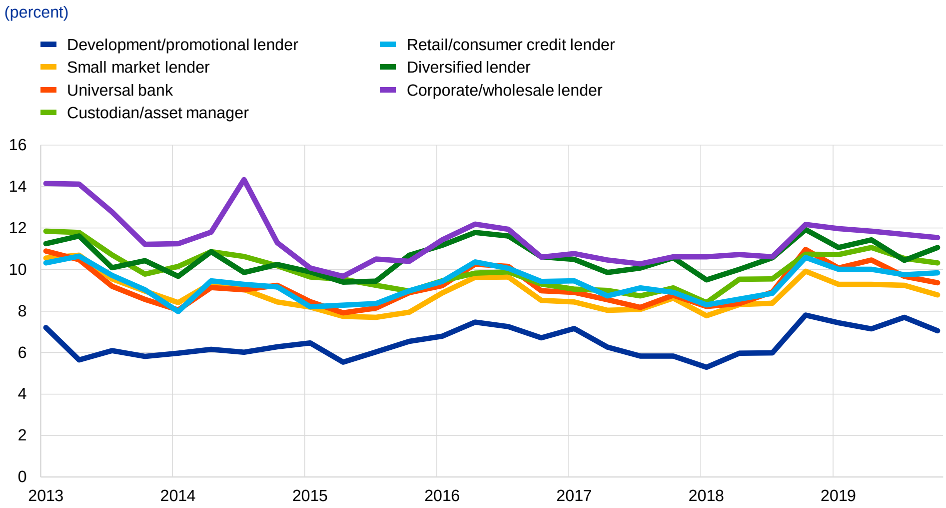
Notes: Quarterly data. Both aggregates weighted by book value of equity for comparability. Latest observation: December 2019.

5.3 Results

On aggregate, the COE of unlisted banks is marginally lower than that of their listed peers, while the range of bank-level estimates is wider (Chart 13). The estimates of unlisted banks peak in 2008 and again in 2011-12. Also, the range of bank-level estimates widens, as our methodology takes explicitly into account the uncertainty introduced by the regressions that we estimate (compare Chart 14 to Chart 10).

Chart 14

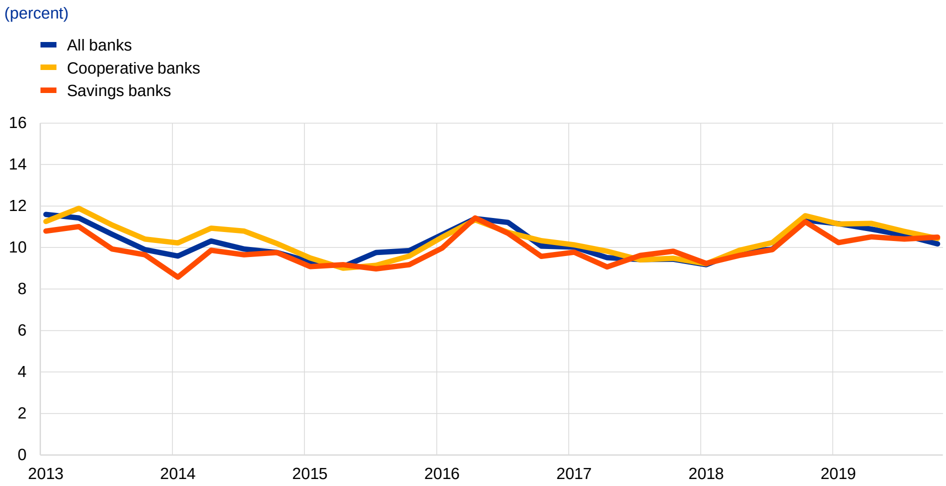
Cost of equity estimates for unlisted euro area banks by business model



Notes: Quarterly data. Aggregates weighted by book value of equity. Latest observation: December 2019.

Chart 15

Cost of equity estimates for euro area banks by ownership status



Notes: Quarterly data. Aggregates weighted by book value of equity. Latest observation: December 2019.

Development/promotional lenders have a distinctly lower cost of equity than other unlisted banks, in line with the survey findings (Chart 14). Unlisted banks span a wider range of business models, which also tend to be more specialised than the larger, more diversified, listed euro area banks. Among them, development/promotional lenders stand out due to their low cost of equity, which stems from their solid capital structure, high asset quality and increased cost efficiency. At the other side of the spectrum, corporate/wholesale lenders, with relatively low cost efficiency and higher reliance on interbank funding, as well as diversified lenders, whose asset quality has suffered, stand out as the business models with highest average cost of equity over the period examined.

We find no material differences in the estimated cost of equity by ownership status (Chart 15). A number of banks in Europe are not private corporations, but rather operate as cooperative or savings banks. Mission statements of such banks often emphasise objectives other than shareholder value maximisation. That could lead to systematic differences in the cost of equity, as the owners of these banks often require lower returns. As these banks are unlisted, the interpretation of this finding is that the fundamentals of these banks would, on average, imply a cost of equity that is indistinguishable from that of the entire bank universe.

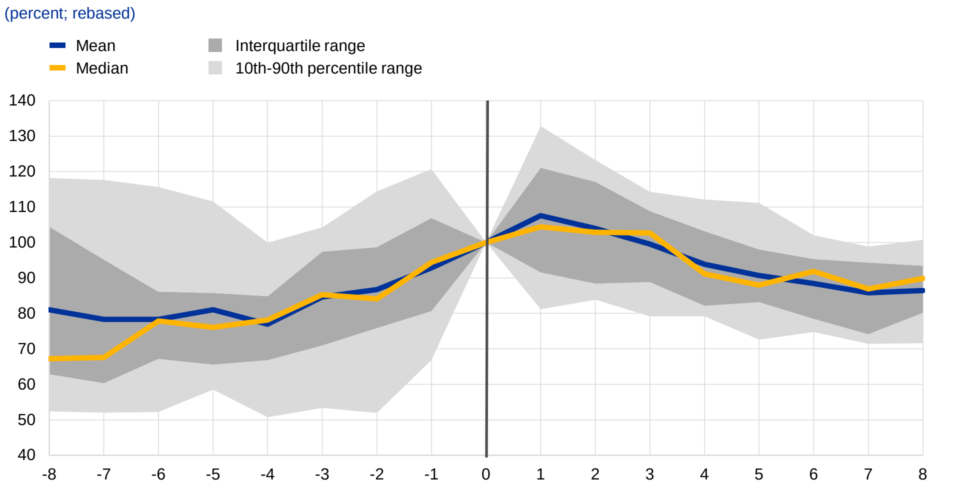
6 Additional evidence

6.1 Backtesting using failure events

One element of interest regarding the estimated results discussed in previous sections is how banks' cost of equity behaves during periods of distress. For that purpose, we applied a comprehensive dataset of individual banks' distress cases in the EU to our bank-level cost of equity estimates in an event-study-type setup. The dataset used in this analysis was originally used for the application of early warning modelling for European banks (see Lang, Peltonen and Sarlin, 2018). It covers four types of distress events: i) receiving State aid, ii) distressed mergers, iii) defaults, and iv) bankruptcies. In total, 25 distress events of individual banks were identified for our sample of listed banks.

Chart 16

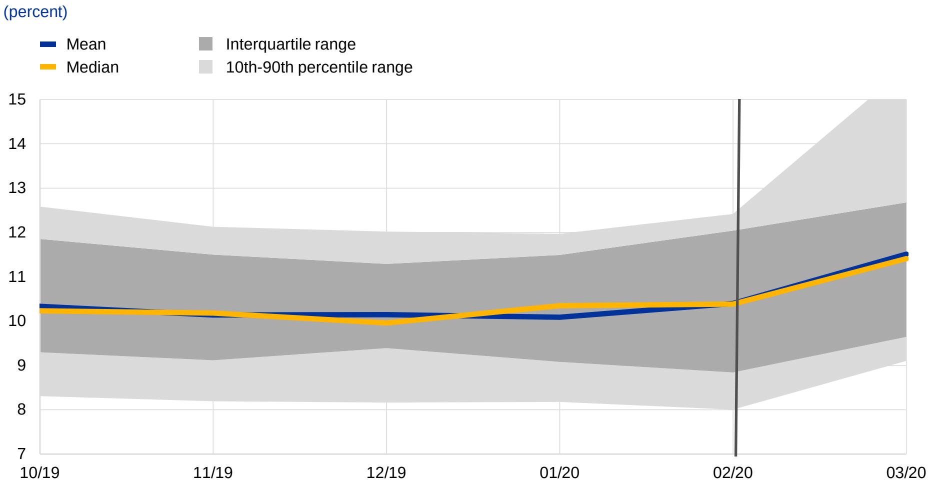
Cost of equity estimates around distress events



Sources: Bloomberg, Refinitiv, European Commission, Moody's Fitch, Bankscope, Kenneth French's data library, IMF World Economic Outlook and ECB calculations.
Note: COEs for Individual firms are rebased to a value of 100 at their respective distress dates.

Chart 17

Cost of equity estimates around the COVID-19 outbreak



Sources: Bloomberg, Refinitiv, Kenneth French's data library IMF World Economic Outlook and ECB calculations.
Note: Quarterly data. Aggregates weighted by book value of equity.

Cost of equity seems to anticipate bank distress, with a lead time of about one year. The average COE of banks for which a distress event was identified increases monotonically, starting around four quarters before the distress date, and reaches its peak in the quarter following the identified distress event (Chart 16). On average, the COE estimate in the distress quarter is around 30 percent higher compared to the level before the start of the increase. Noticeably, the COE tends to remain elevated for several quarters after the distress date.

Cost of equity also appears to have increased with the outbreak of the COVID-19 pandemic. Chart 17 displays the developments of monthly bank-level COE estimates around the outbreak of the COVID-19 crisis. The horizontal line marks the end February 2020 – the beginning of the global market correction. The chart clearly documents the increase in COE at the end of February and particularly at the end of March.

6.2 Comparison of estimated cost of equity and CoCo yields

As a plausibility check, we compared the estimated cost of equity to the yields of contingent convertible capital instruments (CoCos).[21] CoCos are a form of hybrid debt, which was introduced after the financial crisis to serve as an additional source of equity capital in adverse times. This occurs through an activation mechanism that either happens mechanically, once a pre-defined trigger in the form of a specified CET1 ratio is reached, or on instruction by the regulator at the point of non-viability[22]. Currently, two types of CoCos exist, depending on the action taken in the event of activation, namely those that feature equity conversion and those that

[21] See Avdjiev, Kartasheva and Bogdanova (2013) for an introduction to CoCos.

[22] See Glasserman and Perotti (2017) on how the mechanical trigger constitutes a de facto discretionary regulatory decision.

incur a write down. We have restricted our analysis to the first type of CoCos as this keeps to the traditional rules of seniority under the SRM regulation.[23]

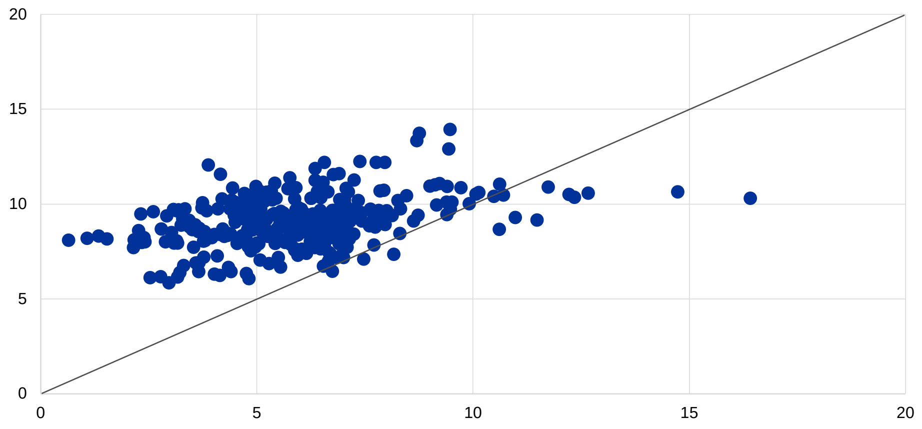
The yield on CoCos with equity conversion represents a strict lower bound to the cost of equity. CoCos are the riskiest type of debt a bank can issue that is ranking higher in seniority – and is less volatile – than equity.[24] For that reason, the yield on CoCos should generally be lower than the estimated cost of equity.

For any given bank and point in time, our cost of equity estimates are higher than the respective CoCo yields in 95% of the cases, adding to the plausibility of our estimates (Chart 18). The remaining 5 percent can be attributed to periods in which the CoCo market experienced upheaval due to uncertainty surrounding the product's modalities. (e.g. the unexpected postponement of calling back the CoCo). We further confirmed that the volatility of CoCo bonds is significantly lower than that of equity in our sample (1.75% versus 6.35% annualised[25]). However, this comparison was only possible for seven banks which have issued CoCos featuring a conversion mechanism. It might therefore be affected by bank-specific factors which are difficult to capture.

Chart 18

Estimated cost of equity vs yields of CoCos featuring equity conversion

(percent)



Notes: 332 monthly observations for seven banks for the period Q1 2014 to Q4 2019. The x-axis shows CoCo yields and the y-axis shows cost of equity.

[23] See Hesse (2018) for an empirical analysis on the premium on write down CoCos compared to equity conversion CoCos.

[24] SRM regulation N. 806/2014, article 21, protects CoCo holders from higher losses than equity holders.

[25] The period between January 2014 and December 2019 was examined. Volatility was weighted by the notional amount in the case of multiple issuances and weighted by the book value of equity across issuers.

7 Conclusions

This paper concludes that, based on a three-step approach combining multiple models of bank cost of equity, the premia investors demand as compensation for the risk they bear when holding banks' equity has been persistently higher than the return on equity generated by banks since the onset of the 2008 financial crisis. Our models point to a median cost of equity of euro area banks of close to 10%. Differences in regulatory treatment and bank strategies related to retained earnings may significantly influence this value. After accounting for estimation and parameter uncertainty, as well as cross-sectional variation, a plausible range for the aggregate cost of equity for euro area banks currently lies between 7.7% and 12.7%, slightly higher than the range of internal estimates of the cost of equity reported by banks to the supervisors.

This paper also finds that banks' estimated cost of equity is related to the fundamentals of the banks, and that the shape of this relationship is in line with economic theory. Banks which hold more non-performing loans also have a higher cost of equity, reflecting the elevated credit risk that they are exposed to. Similarly, banks relying more heavily on the less stable wholesale funding market and banks which are less cost-efficient also face a higher cost of equity.

The cost of equity of unlisted banks appears to be somewhat lower than for listed banks, partly reflecting differences in business models. Estimates for unlisted banks are imputed from a relationship between the cost of equity and fundamentals that can be inferred for listed banks. The lower cost of equity for unlisted banks is to some extent explained by the presence of government-owned promotional and development banks in the sample of unlisted banks. Such institutions tend to be less risky than other banks, and given their public-policy objectives, the government shareholder may expect them to generate lower returns. Among other banks, there is no systematic difference between the cost of equity of commercial, savings, and cooperative unlisted banks.

These conclusions are relevant for prudential policy as well as for monetary policy, showing that banks need to take action to sustainably improve their profitability to the required level implied by their cost of equity. This might be achieved by reducing operational inefficiencies, which may entail up-front costs but would both improve profitability and durably reduce the cost of equity in the longer run. Also, they need to make sure that their pricing of new loans and the funding mix that they choose generate profits that compensate them adequately for the risks they take. Such actions would contribute to narrowing the observed gap between returns on equity and cost of equity.

As a general caveat, the interpretation of differences between the cost of equity and the return on equity warrants some caution in view of the large parameter and estimation uncertainties found in the empirical analysis. Our results also suggest that estimates of the cost of equity for individual banks tend to be imprecise, with large standard errors, explicitly signalling a high degree of uncertainty in the results obtained. Estimates of the cost of equity at a more aggregated level (country or euro area level) ought to be more precise.

References

Abudy, M., Benninga, S., and Shust, E. (2016), “The cost of equity for private firms”, *Journal of Corporate Finance*, Vol. 37, pp. 431-443.

Acharya, V., Drechsler, I., and Schnabl, P. (2014), “A pyrrhic victory? Bank bailouts and sovereign credit risk”, *Journal of Finance*, Vol. 69, No 6, pp. 2689-2739.

Adrian, T., Friedman, E., and Muir, T. (2016), “The cost of capital of the financial sector”, *Federal Reserve Bank of New York Staff Reports*, No 755.

Altavilla C., Boucinha M., and Peydro J.-L. (2018), “Monetary policy and bank profitability in a low interest rate environment”, *Economic Policy*, Vol. 33, No 96, pp. 531-586.

Andreeva, D., Grodzicki, M., Móré, C., and Reghezza, A. (2019), “Euro area bank profitability: where can consolidation help?”, Special feature in *Financial Stability Review,* European Central Bank, November 2019, pp. 107-118.

Andersson, M., Kok, C., Mirza, H., Móré, C., and Mosthaf, J. (2018), “How can euro area banks reach sustainable profitability in the future?”, Special feature in *Financial Stability Review,* European Central Bank, November 2018, pp. 125-142.

Armstrong, J.S. (2001), *Principles of forecasting: A handbook for researchers and practitioners, Kluwer Academic Publishers*, United States.

Avdjiev, S., Kartasheva A., and Bogdanova, B. (2013), “CoCos: a primer”, *BIS Quarterly Review*, Bank for International Settlements, Basel, September.

Bali, T.G., and Engle, R. (2010), “The intertemporal Capital Asset Pricing Model with dynamic conditional correlations*”, Journal of Monetary Economics*, Vol. 57, No 4, pp. 337-390.

Barber, B.M., and Lyon, J.D. (1997), “Firm size, book-to-market ratio, and security returns: A holdout sample of financial firms”, *Journal of Finance*, Vol. 52, No 2, pp. 875-883.

Barnes, M.L., and Lopez, J.A. (2006), “Alternative measures of the Federal Reserve Banks’ cost of equity capital”, *Journal of Banking & Finance*, Vol. 30, No 6, pp. 1687-1711.

Bekaert, G., Harvey, C. (2000).” Foreign speculations and emerging equity markets”, *Journal of Finance*, Vol. 55, pp. 565–613.

Berndt, A., Duffie, J.D., and Zhu, Y. (2020), “The decline of too big to fail”, unpublished paper.

Bessler, W., and Kurmann, P. (2014), “Bank risk factors and changing risk exposures: Capital market evidence before and during the financial crisis”, *Journal of Financial Stability*, Vol. 13, Issue C, pp. 151-166.

Bogdanova, B., Fender, I., and Takáts, E. (2018), “The ABCs of bank PBRs”, *BIS Quarterly Review*, Bank for International Settlements, Basel, March, pp. 81-95.

Boubakri, N., Guedhami, O., Mishra, D. (2010), “Family control and the implied cost of equity: evidence before and after the Asian financial crisis”, *Journal of International Business Studies*, Vol. 41, No 3, pp. 451-474.

Boubakri, N., Guedhami, O., Mishra, D., and Saffar, W. (2012), “Political connections and the cost of equity capital”, *Journal of Corporate Finance*, Vol. 18, No 3, pp. 541-559.

Boucinha, M., Holton, S., and Tiseno, A. (2017), “Bank equity valuations and credit supply”, Working paper.

Bruner R.F., Eades, K.M., Harris, R.S., and Higgins, R.C. (1998), “Best practices in estimating the cost of capital: Survey and synthesis”, *Financial Practice and Education*, Vol. 8, No 1, pp. 13-28.

Chen, K., Chen, Z., and Wei, K. (2011), “Agency costs of free cash flow and the effect of shareholder rights on the implies cost of equity capital”, *Journal of Financial and Quantitative Analysis*, Vol. 46, No 1, pp. 171-207.

Claus, J., and Thomas, J. (2001), “Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets”, *Journal of Finance*, Vol. 56, No 5, pp. 1629-1666.

Clemen, R.T. (1989), “Combining forecasts: A review and annotated bibliography”, *International Journal of Forecasting*, Vol. 5, No 4, pp. 559-583.

Cochrane, J.H. (2005), “Regression-based tests of linear factor models”, *Asset pricing,* Revised edition, Princeton University Press, New Jersey, pp. 229-251.

Damodaran, A. (2017), Equity Risk Premiums (ERP): Determinants, estimation and implications – The 2017 edition, unpublished paper.

Dhaliwal, D., Krull, L., Li, O.Z. (2007), “Did the 2003 Tax Act reduce the cost of equity capital?”, *Journal of Accounting and Economics*, Vol. 43, No 1, pp. 121-150.

Demirgüç-Kunt, A., and Huizinga, H. (2013), “Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads”, *Journal of Banking & Finance*, Vol. 37, pp. 875–894.

Dick-Nielsen, J., Gyntelberg J., and Thimsen, C. (2019), “The cost of capital for banks: evidence from analyst earnings forecasts”, unpublished paper.

Easton, P. (2004), “PE Ratios, PEG Ratios, and estimating the implied expected rate of return on equity capital”, *Accounting Review*, Vol. 79, No 1, pp. 73-95.

El Ghoul, S., Guedhami, O., Kwok, C., and Mishra, D. (2011), “Does corporate social responsibility affect the cost of equity capital?” *Journal of Banking and Finance,* Vol. 35, No 9, pp. 2388-2406.

Elton, E.J., Gruber, M.J., and Mei, J. (1994), “Cost of capital using the arbitrage pricing theory”, *Financial Markets, Institutions and Instruments*, Vol. 3, No 3, pp. 46-73.

Engle, R. (2016), “Dynamic conditional beta”, *Journal of Financial Econometrics*, Vol. 14, No 4, pp. 643-667.

Engle, R. (2002), “Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models”, *Journal of Business & Economic Statistics*, Vol. 20, No 3, pp. 339-350.

European Central Bank (2011), “Common equity capital, banks’ riskiness and required return”, *Financial Stability Review*, December, pp. 125-131.

European Central Bank (2015), “Measuring the cost of bank equity in the euro area”, *Financial Stability Review*, May, pp. 61-63.

European Central Bank (2016), “Estimation of the cost of equity”, *Economic Bulletin*, Issue 1, pp. 43-45.

European Central Bank (2018), “Measuring and interpreting the cost of equity in the euro area”, *Economic Bulletin*, Issue 4, pp. 79-88.

Fama, E.F., and French, K.R. (1992), “The Cross-Section of Expected Stock Returns”, *Journal of Finance*, Vol. 47, No 2, pp. 427-465.

Fama, E.F., and French, K.R. (1993), “Common risk factors in the returns on stocks and bonds”, *Journal of Financial Economics*, Vol. 33, No 1, pp. 3-56.

Fama, E.F., and French, K.R. (1997), “Industry costs of equity”, *Journal of Financial Economics*, Vol. 43, No 2, pp. 153-193.

Frazzini, A., and Pedersen, L.H. (2014), “Betting against beta”, *Journal of Financial Economics,* Vol. 111, No 1, pp. 1-25.

Gandhi, P., and Lustig, H. (2015), “Size anomalies in U.S. bank stock returns”, *Journal of Finance*, Vol. 70, No 2, pp. 733-768.

Gebhardt, W.R., Lee, C.C., and Swaminathan, B. (2001), “Toward an implied cost of capital”, *Journal of Accounting Research*, Vol. 39, No 1, pp. 135-176.

Girotti, M. and Horny, G. (2020), "Bank equity value and loan supply," *Working papers 767*, Banque de France.

Glasserman, P., and Perotti, E. (2017), “The Unconvertible CoCo Bonds”, in Kaufman, G. G., Leonelo, A., Manganelli, S., Evanelli, D. (eds.), *Achieving Financial Stability: Challenges to Prudential Regulation*, World Scientific, Singapore, pp. 317-329.

Gode, D., and Mohanram, P. (2003), “Inferring the cost of capital using the Ohlson–Juettner model”, *Review of Accounting Studies*, Vol. 8, pp. 399-431.

Gode, D., and Mohanram, P. (2013), “Removing predictable analyst forecast errors to improve implied cost of equity estimates*”, Review of Accounting Studies*, Vol.18, pp. 443–478.

Goel, T., Lewrick, U., and Mathur, A. (2019), “Playing it safe: global systemically important banks after the crisis”, *BIS Quarterly Review*, September 2019, pp. 35-47.

Goldenberg, D.H., and Robin, A.J. (1991), “The arbitrage pricing theory and cost-of-capital estimation: The case of electric utilities”, *Journal of Financial Research*, Vol. 14, No 3, pp. 181-196.

Green, E.J., Lopez, Green, E.J., and Wang, Z. (2003), “Formulating the imputed cost of equity capital for priced services at Federal Reserve banks”, *Federal Reserve Bank of New York Economic Policy Review*, Vol. 9, No 3, pp. 55-81.

Grodzicki, M., Rodriguez d’Acri, C., and Vioto, D. (2019), “Recent developments in banks’ price-to-book ratios and their determinants”, *Financial Stability Review*, European Central Bank, May, pp. 66-69.

Hail, L., and Leuz, C. (2006), “International differences in cost of equity capital: do legal institutions and securities regulations matter?”*, Journal of Accounting Research*, Vol.44, No 3, pp. 485-531.

Hail, L., and Leuz, C. (2009), “Cost of capital effects and changes in growth expectations around U.S. cross-listings”*, Journal of Financial Economics*, Vol. 93. No 3, pp. 428-454.

Hesse, H. (2018), “Incentive effects from write-down CoCo bonds: an empirical analysis”, *SAFE Working Paper Series*, No 212, Leibniz Institute for Financial Research SAFE.

Huljak, I., Martin, R., and Moccero, D. (2019), “The cost-efficiency and productivity growth of euro area banks”, *ECB Working Paper Series*, No 2305, European Central Bank, Frankfurt am Main, August.

Kartashova, K. (2014), “Private equity premium puzzle revisited”, *American Economic Review*, Vol. 104, No 10, pp. 3297-3334.

Kovner, A., and Van Tassel, P. (2019), “Evaluating Regulatory Reform: Banks’ Cost of Capital and Lending”, *Federal Reserve Bank of New York Staff* Reports 854, June 2018, Revised May.

Lang, J.H., Peltonen, T.A., and Sarlin, P. (2018), “A framework for early-warning modelling with an application to banks”, *ECB Working Paper Series*, No 2182, European Central Bank, Frankfurt am Main, October.

Levi, Y., and Welch, I. (2017), “Best practice for cost-of-capital estimates”, *Journal of Financial and Quantitative Analysis*, Vol. 52, No 2, pp. 427-463.

Lintner, J. (1965), "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets", *The Review of Economics and Statistics*, Vol. 47, No 1, pp. 13-37.

Markowitz, H. (1952), "Portfolio selection", *Journal of Finance*, Vol. 7, No 1, pp. 77-91.

Moskowitz, T., and Vissing-Jørgensen, A. (2002), "The returns to entrepreneurial investment: a private equity premium puzzle?", *American Economic Review*, Vol. 92, Issue 4, pp. 745-78.

Mossin, J. (1966), "Equilibrium in a capital asset market", *Econometrica*, Vol. 34, No 4, pp. 768-783.

Ohlson, J.A., and Juettner-Nauroth, B.E. (2005), "Expected EPS and EPS growth as determinants of value", *Review of Accounting Studies*, Vol. 10, pp. 349-365.

Pastor, L., Sinha, M., and Swaminathan, B. (2008), "Estimating the inter-temporal risk-return tradeoff using the implied cost of capital", *Journal of Finance*, Vol. 63, No 6, pp. 2859-2897.

Ross, S.A. (1976), "The arbitrage theory of capital asset pricing", *Journal of Economic Theory*, Vol. 13, No 3, pp. 341-360.

Rostagno, M., Altavilla, C., Carboni, G., Lemke, W., Motto, R., Saint-Guilhem, A., and Yiangou, J. (2019), "A Tale of two Decades: The ECB's Monetary Policy at 20", *ECB Working Paper Series*, No 2346.

Rubin, D.B. (1987), *Multiple imputation for nonresponse in surveys*, Wiley, New York.

Schuermann, T., and Stiroh, K.J. (2006), "Visible and hidden risk factors for banks", *FRB of New York Staff Report*, No 252, Federal Reserve Bank of New York.

Sharpe, W.F. (1964), "Capital asset prices: A theory of market equilibrium under conditions of risk", *Journal of Finance*, Vol. 19, No 3, pp. 425-442.

So, E.C. (2013), "A new approach to predicting analyst forecast errors: do investors overweight analyst forecasts?", *Journal of Financial Economics*, Vol. 108, No 3, pp. 615-640.

Timmerman, A. (2006), "Forecast Combinations", in Elliott, G., Granger, C. and Timmermann, A. (eds.), *Handbook of Economic Forecasting*, Elsevier, San Diego, pp. 135-196.

Vasicek, O.A. (1973), "A note on using cross-sectional information in Bayesian estimation of security betas", *Journal of Finance*, Vol. 28, No 5, pp. 1233-1239.

Véron, N. (2017), "The governance and ownership of significant euro-area banks", *Bruegel Policy Contribution*, Issue No 14.

Appendix

A.1 Robustness of factor models

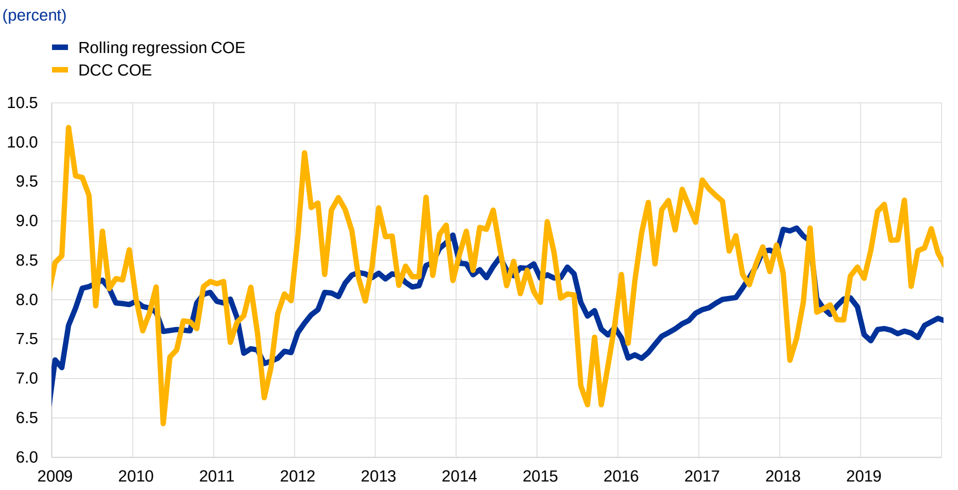
The choice of econometric modelling techniques in the context of factor models can have significant implications for the resulting cost of equity estimates. First, as described in Section 3.1, employing the dynamic conditional correlations (DCC) approach in the area of factor models allows for instantaneous estimates of time varying beta coefficients. While the DCC approach was developed by Engle on the basis of multivariate GARCH models around the turn of the millennium, its application to factor models and the estimation of betas has found its way into the financial literature only recently.[26] Therefore, it makes sense to compare our results to more widely used standard methodologies incorporating time varying parameters.

One of the most common approaches is the rolling window estimation. Despite its apparent conceptual flaws, such as employing an inconsistent set of assumptions, it is frequently applied in the literature due to its simplicity: it uses OLS regressions on evolving windows of a certain length. Rolling regressions therefore aim at estimating betas based on historical volatilities and correlations of an often arbitrarily chosen window of data. On the one hand, the assumption that current returns are described with equal probability by any returns of the past k days (depending on the chosen window length), but not from returns further than k days in the past, seems unrealistic. On the other hand, relying on this type of historical data of a certain window length necessarily introduces a certain lag and smoothing to the estimates. Chart A.1 compares the cost of equity based on beta estimates obtained from two-year rolling window regressions to the estimates obtained from the DCC approach.

[26] E.g. Engle (2016): Dynamic Conditional Beta.

Chart A.1

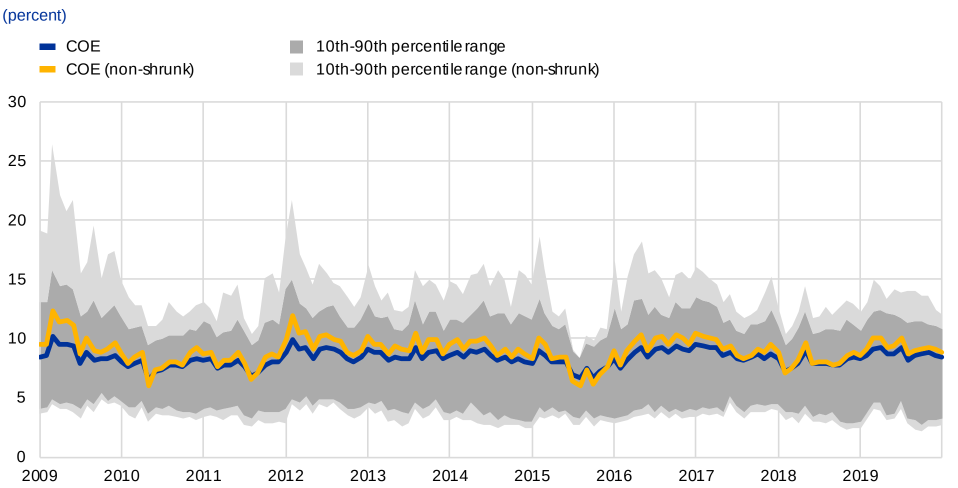
COE estimated from the DCC approach is more timely than rolling-regression estimates



Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Note: The lines show the average COE estimates of the five factor models at a weekly frequency.

Chart A.2

COE based on shrunk beta estimates preserve the central tendency but show more plausible cross-sectional ranges



Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Note: End of month observations.

While the levels and dynamics of both time series are similar, both the smoothing and lagging properties of the rolling window estimation are clearly visible. In contrast, the DCC approach directly obtains betas from time-varying variance-covariance matrices estimated over the entire data sample, and therefore provides instantaneous coefficient estimates. This allows for a more timely reaction of parameters to current developments.

Second, transforming beta estimates using a version of the Vasicek (1973) Bayesian shrinkage factor ensures that the results minimise the loss due to

mis-estimation by incorporating cross-sectional information. This results in estimates such that given the sample information, the true betas will, with equal probability, lie below or above them. Chart A.2 displays simple averages of the COE estimates from shrunk and non-shrunk betas, as well as the 10th–90th percentile range of the bank level estimates. It is evident that the volatility of the shrunk bank level estimates is distinctly reduced, while the averages show only minor differences. Therefore, the transformed betas allow for more reliable estimates at individual bank level, while broadly retaining the central tendency of cross-sectional information.

A.2 Data appendix for factor models

COE estimates for dynamic portfolio sorts and individual firms are based on a comprehensive sample of listed euro area banks. Utilising Bloomberg's equity-screening function, banks are identified by applying the Bloomberg Industry Classification Standard and filtering for primary securities of publicly-traded banks for which stock price data are available at some point in time during the period from January 2000 to December 2019. Only banks incorporated in countries that initially adopted the euro in 1999 are considered and smaller economies with only a small number of traded banks are excluded. We also excluded banks with a percentage of free-floating shares below 25% to account for government ownership and subsidiaries.

For dynamic portfolio sorts and bank-level estimates, we used stock price data with daily frequency obtained from Bloomberg. Missing stock price data related to public holidays were replaced by previous daily observations. Other missing observations were replaced by interpolated values between the previous daily observation in that week and the next. Daily data were then converted into weekly returns using end-of-week observations. Only banks with at least one year of continuous weekly stock price data were used to compute weekly returns. In addition, only banks with a total of no more than four consecutive zero return weeks were kept in the sample. The sample was further truncated using a floor of €1 billion average market capitalisation over the total period to reduce the impact of small and possibly illiquid stocks, and returns are winsorised at the lower 0.1 percent and the upper 99.9 percent levels.

For the estimation of dynamic size and value portfolio sorts we obtained firm-level data of market capitalisation and book value of equity per share from Bloomberg. We used market capitalisation data of daily frequency converted into a weekly frequency using end-of-week observations. Any missing data were imputed from the associated stock price and the previous available market capitalisation observation. Data on book value of equity for the calculation of price-to-book ratios was obtained using point-in-time (at the date of publication) data at the shortest available interval for each respective bank.[27] Data were carried forward by a

[27] Using point-in-time financial reporting data makes the use of a reporting lag in the computation of portfolios unnecessary as data is only available from the actual date the data was made public. In addition, using an unbalanced sample of banks and including liquidated and merged companies as well as those (re-)entering the public stock market eliminates potential survivorship bias.

maximum of two years. From the firm-level data, we constructed nine market capitalisation-weighted time series of portfolio returns as the intersections of conditional three by three size and price-to-book sorts. Portfolios are rebalanced once a year in June. First, stocks were sorted into one of three portfolios, depending on the terciles of market capitalisation in t-1. Then, portfolios of price-to-book terciles (also in t-1) were formed, conditional on the stocks contained in the size portfolios.[28] We used conditional sorts to avoid large dispersions in the number of banks across portfolios. We then computed the market capitalisation-weighted returns of these nine portfolios.

For country-level and euro area-level estimates, we used weekly returns of bank stock indices in excess of the risk-free rate. Bank index data were based on end-of-week prices of market capitalisation-weighted bank stock price indices provided by Refinitiv Datastream for each respective country and the euro area.

Aggregate euro area data were used for the approximation of risk factors. We used weekly excess returns calculated from daily index values of Refinitiv's broad euro area equity price index as a proxy of the market risk factor.[29] The daily time series of the two European factors for the Fama-French three factor model were downloaded from Kenneth French's data library[30] and transformed into weekly returns. We used the weekly return difference between euro-denominated total-return bond indices of BBB and AA-rated corporate bonds with a residual maturity of 7-10 years for approximation of the credit risk factor. The sovereign risk factor is calculated as the return difference between equal-weighted Spanish, Italian and Portuguese total-return sovereign-bond indices and the equivalent German-bond index (all 7-10 years' residual maturity). All bond data were obtained from the ICE BofA Fixed Income Indices.

A.3 Beta estimates and risk premia for factor models

This section provides additional results from multi-factor models, in particular beta estimates for banking-sector indices of euro area countries and portfolio indices obtained through dynamic portfolio sorts based on banks' size and price-to-book ratios.

The explanatory power as measured by the adjusted R-squared is high across models for the euro area banking sector index and the larger country indices (see Table A.2). For smaller counties, the measure tends to be distinctly lower, reflecting the importance of idiosyncratic risks for smaller banking systems. Estimates of the pricing error (alpha) were very close to zero and insignificant for the majority of countries.

28 As financial reporting data in our data set is already point-in-time, there is no need for additional lags. Therefore, it is sufficient to assume that portfolio decisions related to weekly returns at date t are made on the basis of data available at date t-1.

29 The index covers around 1450 stocks from different industries within the euro area. Excess returns are calculated over weekly returns of the one year euro OIS rate.

30 Fama-French factors from the data library of Kenneth French.

The market beta is highly significant for all models and jurisdictions but is distinctly lower after the inclusion of additional factors, pointing to a possible omitted variable bias of the CAPM. The HML factor has a significantly positive coefficient (with the exception of the Netherlands (NL), where it is insignificant) and is above one for most jurisdictions. This result indicates that the returns of banks in these banking systems behave similarly to those of firms with a low price-to-book ratio[31] – that is possibly undervalued or distressed firms. The SMB factor is insignificant for most banking systems, indicating that the returns of these banks do not behave like the typical small-cap (non-financial) firm. We find two exceptions: for Portugal (PT), the coefficient is significant and close to one, and for Spain (ES), the coefficient is significantly negative. The results from the model with the corporate and sovereign credit factors are as follows: both factors are positive and significant for the euro area aggregate, but the significance of BBB and SOV varies across countries. The coefficient for SOV is positive and significant for most countries, and tends to be higher for countries more affected by the euro area sovereign-debt crisis. However, its coefficient is significantly negative in NL (where sovereign debt markets benefited from flight-to-safety during periods of elevated sovereign distress) and insignificant and close to zero for Germany.

When banks are sorted into portfolios by their size and P/B ratio, we find that beta estimates for Fama-French factors and the model with credit variables relate to each other meaningfully. The explanatory power of the factor models decreases with firm size, a common finding in the empirical asset pricing literature. The market beta also decreases with firm size, but is highly significant across portfolios and models. The risk-exposure estimates for SMB are insignificant for the largest banks but significant for all other portfolios, with an average of 0.69 for mid-sized banks and 0.77 for the smallest banks. The HML factor is significantly positive for all portfolios but increases distinctly for portfolios with a lower P/B ratio, up to an average of 1.61 for the portfolios with the lowest P/B ratio. These findings confirm that euro area bank's size and P/B ratios relate meaningfully to the corresponding Fama-French factors. For the model with credit factors, we also observe an increase of the market beta with bank size, while the BBB and SOV beta estimates appear to increase for banks with a lower valuation. This could indicate that banks' low valuations are to some extent driven by pronounced exposures to sovereign and credit risk. We therefore conclude that beta estimates for these credit variables correlate meaningfully to the betas obtained from Fama-French factors.

[31] To be noted that Fama and French (1992) employ the ratio of book-to-market (B/M) to define their HML factor, while in this paper we base the discussion on the price-to-book ratio (P/B), i.e. the inverse of B/M.

Table A.1

Static beta estimates for portfolio sorts

(coefficients, standard errors, adjusted R2)

	Large, high P/B	Large, medium P/B	Large, low P/B	Medium, high P/B	Medium, medium P/B	Medium, low P/B	Small, high P/B	Small, medium P/B	Small, low P/B
					CAPM				
Alpha	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MKT	1.37*** (0.05)	1.55*** (0.08)	1.65*** (0.07)	1.04*** (0.04)	1.14*** (0.07)	1.43*** (0.08)	0.65*** (0.04)	0.71*** (0.04)	0.91*** (0.07)
Adj. R2	0.68	0.68	0.68	0.60	0.49	0.38	0.36	0.40	0.26
					Model with Fama-French factors				
Alpha	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MKT	1.15*** (0.06)	1.14*** (0.07)	1.25*** (0.06)	0.96*** (0.06)	0.94*** (0.07)	1.38*** (0.11)	0.77*** (0.05)	0.71*** (0.05)	0.93*** (0.08)
SMB	-0.16 (0.18)	-0.24 (0.27)	0.08 (0.21)	0.49*** (0.12)	0.50*** (0.15)	1.08*** (0.22)	0.71*** (0.14)	0.58*** (0.12)	1.02*** (0.19)
HML	0.83*** (0.12)	1.58*** (0.11)	1.97*** (0.12)	1.02*** (0.08)	1.63*** (0.12)	1.64*** (0.17)	0.37*** (0.10)	0.76*** (0.10)	1.23*** (0.15)
Adj. R2	0.72	0.78	0.81	0.69	0.64	0.48	0.42	0.49	0.36
					Model with credit factors				
Alpha	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)	0.00** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)
MKT	1.31*** (0.07)	1.39*** (0.12)	1.42*** (0.09)	0.85*** (0.06)	0.86*** (0.06)	0.95*** (0.10)	0.60*** (0.05)	0.53*** (0.05)	0.06*** (0.09)
BBB	0.44 (0.32)	0.58 (0.50)	0.54 (0.34)	0.83*** (0.26)	0.61** (0.28)	2.04*** (0.60)	0.29 (0.30)	0.84*** (0.26)	1.52*** (0.47)
SOV	0.08 (0.08)	0.40*** (0.13)	0.72*** (0.13)	0.40*** (0.08)	0.93*** (0.10)	1.06*** (0.19)	0.07 (0.08)	0.38*** (0.08)	0.59*** (0.15)
Adj. R2	0.69	0.70	0.71	0.64	0.57	0.47	0.36	0.45	0.32

Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This table contains beta risk exposure estimates from time series regressions of portfolio indices for banks on risk factors. Portfolios are obtained by dynamically sorting banks according to their size (market value of equity) and then conditionally on their P/B ratio (see Section A.2 for details). The first column displays the largest banks with the (conditionally) highest P/B and the last column displays the smallest banks with the (conditionally) lowest P/B. Regressions are based on weekly data from 19/09/2008 to 27/12/2019, with Newey-West standard errors correcting for serial correlation and heteroscedasticity in parenthesis below the beta estimates. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table A.2

Static beta estimates for banking sector stock indices of euro area countries

(coefficients, standard errors, adjusted R2)

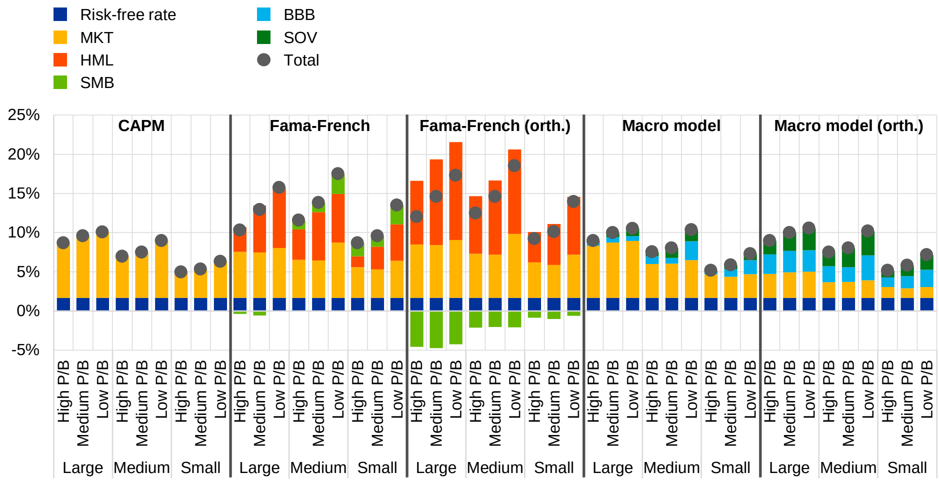
	EMU	AT	BE	DE	ES	FR	IT	NL	PT
CAPM									
Alpha	0.00* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)	0.00 (0.00)	0.00* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)
MKT	1.48*** (0.06)	1.39*** (0.08)	1.74*** (0.11)	1.55*** (0.09)	1.47*** (0.07)	1.57*** (0.1)	1.48*** (0.07)	0.63*** (0.14)	1.20*** (0.09)
Adj. R2	0.72	0.55	0.51	0.58	0.57	0.62	0.58	0.09	0.31
Model with Fama-French factors									
Alpha	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)
MKT	1.13*** (0.05)	1.23*** (0.12)	1.45*** (0.11)	1.28*** (0.10)	1.01*** (0.08)	1.12*** (0.09)	1.11*** (0.07)	0.82*** (0.15)	1.14*** (0.10)
SMB	0.04 (0.15)	0.31 (0.23)	0.51 (0.41)	-0.06 (0.37)	-0.37** (0.15)	-0.21 (0.28)	0.15 (0.16)	0.98 (0.70)	1.04*** (0.23)
HML	1.66*** (0.09)	1.16*** (0.17)	2.05*** (0.28)	1.18*** (0.18)	1.68*** (0.12)	1.82*** (0.15)	1.92*** (0.14)	0.38 (0.47)	1.66*** (0.19)
Adj. R2	0.85	0.61	0.61	0.63	0.67	0.73	0.71	0.12	0.42
Model with credit factors									
Alpha	0.00** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)	0.00 (0.00)	0.00*** (0.00)
MKT	1.26*** (0.07)	1.20*** (0.11)	1.37*** (0.09)	1.53*** (0.13)	1.29*** (0.07)	1.38*** (0.13)	1.20*** (0.07)	0.36 (0.33)	0.79*** (0.09)
BBB	0.73* (0.38)	1.33*** (0.40)	2.69** (1.34)	0.21 (0.43)	-0.01 (0.33)	0.65 (0.63)	0.48* (0.28)	3.48 (2.54)	1.16** (0.54)
SOV	0.57*** (0.10)	0.13 (0.12)	0.24 (0.20)	-0.02 (0.14)	0.80*** (0.13)	0.50*** (0.16)	1.02*** (0.13)	-0.62* (0.32)	1.22*** (0.19)
Adj. R2	0.76	0.57	0.55	0.58	0.61	0.63	0.64	0.18	0.41

Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This table contains beta risk exposure estimates from time series regressions of Refinitiv Datastream's banking sector stock indices for euro area countries on risk factors. EMU refers to the aggregate euro area index. Regressions are based on weekly data from 19/09/2008 to 27/12/2019, with Newey-West standard errors correcting for serial correlation and heteroscedasticity in parenthesis below the beta estimates. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Chart A.3

Static cost of equity decomposition for the euro area banking sector

(percent)



Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: This chart contains COE estimates based on full-sample time series regressions (i.e. static betas) of portfolio indices for banks on risk factors. Portfolios are obtained by dynamically sorting banks according to their size (market value of equity) and then conditionally on their P/B ratio (see previous section for details). Regressions are based on weekly data from 18/09/2009 to 27/12/2019.

We obtained risk estimates of risk premia as the historical time series average of the respective risk factor. This was advisable as the risk factors in each of our models constituted traded returns (see e.g. Cochrane, 2005). In general, long-time series are preferred for this purpose. We chose the adoption of the euro as our starting point, i.e. the time series for the risk premia span the period from January 1999 to December 2019. Table A.3 contains the risk premium estimates.

Table A.3

Long-term risk premia

(percent)

	Risk premium (p.a.)
MKT	5.10%
BBB	1.18%
SOV	1.36%
HML	3.80%
SMB	2.36%

Sources: Bloomberg, Refinitiv, Kenneth French's data library and ECB calculations.
Notes: Risk premia are the annualised averages of monthly time series from January 1999 to December 2019. MKT is in excess of the risk-free rate.

A.4 Models used for the implied cost of equity approach

A.4.1 The free cash flow to equity method

This method relies on a typical discount factor model, where a constant growth of earnings is assumed starting with the 6th year in the future:

$$P_o = \sum_{h=1}^{6} \frac{FCFE_h}{(1+r)^h} + \frac{FCFE_7}{(r-g^L)(1+r)^6}$$

where $FCFE_h$, $h = 1, \dots, 7$, are the expected free cash flows to equity for bank i for the future 7 years. $FCFE_7$ is expected to grow at constant rate g^L for the rest of the bank's life.

Our proxies of expected free cash flows for the first future K years are computed based on the following formula:

$$FCFE_h = \begin{cases} (1-RE)(1-\tau)EPS_h, \text{if } EPS_h > 0 \\ EPS_h, \text{if } EPS_h \leq 0 \end{cases}, h = 1, \dots, K$$

where $K = 4$. RE is the percentage of earnings retained by the bank for reinvestment and τ the marginal tax rate on dividends. As seen in the above formula, we also consider the case of future forecasted losses ($EPS_h \leq 0$).

After the first K years, year-to-year growth rates increase at constant rate a, so that the growth rate in year 6 is equal to the long-term growth rate g^L. Hence, we have: $1 + g^L = (1 + g^{FCFE}_{6-K+i}) \cdot a^{6-K+i}$ and $FCFE_{K+i} = FCFE_K \prod_{j=1}^{i}(1 + a^j g^S)$, where $a = \left(\frac{1+g^L}{1+g^S}\right)^{\frac{1}{6-K-1}}$ and $i = 1$. If the available final year forecast is negative, the last available positive forecast is used and the formula adapted correspondingly.

The marginal tax rate (τ) is set to 26.84%, which is the population-weighted average marginal tax rate on dividends for countries in the euro area for 2019.[32] The retained earnings rate (RE) is fixed to equal 10%. We assume a value for RE so that it does not account for the part of retained earnings used to meet capital constraints, as this is in practice owned by shareholders. As CET1 ratios have been on an upward trend since the financial crisis and investments have tended to stagnate, we believe that shareholders are entitled to a very large part of the earnings. Therefore, we assume this number to be 90%.

A.4.2 The method based on the Ohlson and Juettner-Nauroth (2005) model

Ohlson and Juettner-Nauroth (2005) propose the following model for valuing a firm at a certain point in time:

$$P_0 = \frac{EPS_1}{r} \frac{g^S + r\frac{DPS_1}{EPS_1} - (g^L - 1)}{r - (g^L - 1)},$$

where P_0 is the firm's stock price, EPS_1 are the expected one-year ahead earnings per share, DPS_1 are the expected one-year ahead dividends per share, r is the cost of equity and g^S and g^L are the short and long-term expected growth rates in earnings.

[32] Note that this rate is also close to marginal dividend tax rates in Germany (26.4%) and Italy (26%).

Given P_0, the cost of equity is the solution to the equivalent quadratic equation in r, which employs the notations used in Gode and Mohanram (2003, 2013):

$$r = A + \sqrt{A^2 + \frac{EPS_1}{P_0}[g^S - (g^L - 1)]},$$

$$\text{with } A = \frac{1}{2}\left[(g^L - 1) + \frac{DPS1}{P_0}\right].$$

A.4.3 The simplified method based on the Ohlson and Juettner-Nauroth (2005) model

This simplified Ohlson and Juettner-Nauroth (2005) method was obtained by setting $g^L = 1$ and ignoring dividends, as in Easton (2004), Gode and Mohanram (2013) and Dick-Nielsen et al. (2019):

$$r = \sqrt{\frac{EPS_1}{P_0} g^S},$$

In this equation, g^S is generated as described at the beginning of the section.

A.4.4 The Gebhardt, Lee, and Swaminathan (2001) method

This method relies on the residual income model (like that proposed by Claus and Thomas, as discussed in A.4.5). The cost of equity was obtained as the solution to the following 12th order polynomial equation:

$$P_0 = B_0 + \sum_{h=1}^{12} \frac{(ROE_h - r)B_{h-1}}{(1+r)^h} + \frac{(ROE_{12} - r)B_{11}}{r(1+r)^{11}},$$

where $h = 1, \dots, 12$ years is the forecasting horizon, ROE_h is the h-year ahead expected return on equity, while B_{h-1} is the $(h-1)$-year-ahead expected equity book value, with B_0 being the present book value of equity.

Future book values were obtained using clean surplus accounting, which are changes in the shareholder equity excluding transactions with shareholders (such as share repurchases, dividends, among others):

$$B_h = B_{h-1} + EPS_h - DPS_h,$$

$h = 1, \dots, 11$, with EPS_h and DPS_h being expectations of future earnings and dividends per share. For the present book value, we mainly used the quarterly data provided by Refinitiv Eikon. Where this was missing, it was replaced by annual data provided by Bloomberg.

We used I/B/E/S analysts' forecasts for the first four or less future values of ROE, EPS and DPS. After this period, ROE grows at constant rate from year to year so that it merges into the overall euro area median by year 12. Where any of the first four values of future ROE or any of the first three values[33] of EPS or DPS were missing, replacements were computed using the short-term growth rates applied to the last positive estimates. That was also how we computed all EPS and DPS estimates beyond three years ahead. Short-term growth rates for DPS and ROE were obtained by applying the same methodology used to obtain the EPS short-term growth rate, g^S. For ROE, estimated growth rates can sometimes be negative. Where this was the case, they were replaced with the corresponding values of g^S. In the case of positive or zero values, they were replaced instead with the corresponding values of long-term growth, g^L.

A.4.5 The Claus and Thomas (2001) method

This method also relies on the residual income model and the cost of equity is obtained as the solution to the following 5th order polynomial equation:

$$P_0 = B_0 + \sum_{h=1}^{5} \frac{(ROE_h - r)B_{h-1}}{(1+r)^h} + \frac{(ROE_5 - r)(1+g^L)B_4}{(r-g^L)(1+r)^4},$$

where g^L is computed as stated at the beginning of the section. Besides the order of the polynomial, the only other difference to the Gebhardt, Lee, and Swaminathan (2001) method resides in the fact that the ROE growth rate (g_{ROE}) is assumed to be equal to g^L after 5 years. If g_{ROE} equals ROE short-term growth rate, it is computed based on the future four ROE forecasts. For the fifth year, we have: $ROE_{K+i} = ROE_K \prod_{j=1}^{i}(1 + a^j g_{ROE})$, where $a = \left(\frac{1+g^L}{1+g_{ROE}}\right)^{\frac{1}{5-K-1}}$ and $i = 1$. If the final year available forecast was negative, the last available positive forecast was used and the formula adapted accordingly.

A.5 Regression output for the relationship between model-specific cost of equity estimates and bank characteristics

This appendix contains the regressions that were used in the first step of the estimation of cost of equity for unlisted banks. For each of the ten cost of equity specifications, we ran OLS regressions of the model-specific cost of equity on bank-level characteristics. The relationships were qualitatively similar to those we found for the average cost of equity (Table 2, column 2). This implies that the plausibility of our average estimate carries over to the individual models as well. Table A.4 presents the regression output for the factor models and Table A.5 the output for the implied cost of equity models.

[33] As I/B/E/S EPS and DPS estimates for the fourth year are incredibly sparse, we did not take them into consideration at all here. We did, however, consider the fourth year I/B/E/S estimates for ROE whenever they were available.

Table A.4

Factor models' cost of equity and bank fundamentals

	CAPM	Fama-French	Fama-French (orth.)	Model with credit factors	Model with credit factors (orth.)
CET1 ratio	- (0.018)	-0.131*** (0.033)	-0.145*** (0.033)	-0.085*** (0.022)	-0.108*** (0.023)
NPL ratio	0.002 (0.006)	0.032** (0.013)	0.043*** (0.012)	0.013* (0.007)	0.014* (0.008)
Interbank deposit ratio	0.032*** (0.006)	0.047*** (0.013)	0.047*** (0.013)	0.042*** (0.007)	0.040*** (0.008)
Cost-to-income ratio	0.012*** (0.004)	0.009 (0.008)	0.018** (0.008)	0.012*** (0.004)	0.015*** (0.004)
Log (assets)	0.002*** (0.000)	-0.002** (0.001)	-0.002*** (0.001)	0.002*** (0.000)	0.002*** (0.000)
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Obs.	1134	1105	1134	1116	1134
Adj. R-squared	0.421	0.259	0.310	0.414	0.391

Sources: S&P Market Intelligence, ECB and ECB calculations.
Notes: OLS regressions with robust standard errors. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5

Implied cost of equity and bank fundamentals

	GLS	FCFE	OJ	CT	OJS
CET1 ratio	-0.096 (0.065)	-0.095* (0.049)	-0.067 (0.056)	0.000 (0.055)	-0.217*** (0.064)
NPL ratio	0.198*** (0.021)	0.046** (0.023)	0.101*** (0.020)	0.097*** (0.019)	0.267*** (0.021)
Interbank deposit	0.080*** (0.019)	0.087*** (0.016)	0.064*** (0.019)	0.073*** (0.019)	-0.025 (0.023)
Cost-to-income ratio	0.080*** (0.013)	0.024** (0.011)	0.027*** (0.010)	0.036*** (0.011)	0.140*** (0.020)
Log (assets)	0.005*** (0.001)	0.007*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	-0.001 (0.001)
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Obs.	986	971	1022	986	1021
Adj. R-squared	0.520	0.467	0.440	0.269	0.561

Sources: S&P Market Intelligence, ECB and ECB calculations.
Notes: OLS regressions with robust standard errors. Standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Acknowledgements
We would like to thank Pereira Márcia, Federica Mascolo, and Alessia Scudiero for their editing assistance.

Carlo Altavilla
European Central Bank, Frankfurt am Main, Germany; email: carlo.altavilla@ecb.europa.eu

Paul Bochmann
European Central Bank, Frankfurt am Main, Germany; email: paul.bochmann@ecb.europa.eu

Jeroen De Ryck
European Central Bank, Frankfurt am Main, Germany; email: jeroen.de_ryck@ecb.europa.eu

Ana-Maria Dumitru
Deutsche Bundesbank, Frankfurt am Main, Germany; email: ana.dumitru@bundesbank.de

Maciej Grodzicki
European Central Bank, Frankfurt am Main, Germany; email: maciej.grodzicki@ecb.europa.eu

Heinrich Kick
European Central Bank, Frankfurt am Main, Germany; email: heinrich.kick@ecb.europa.eu

Cecilia Melo Fernandes
European Central Bank, Frankfurt am Main, Germany; email: cecilia.melo_fernandes@ecb.europa.eu

Jonas Mosthaf
European Central Bank, Frankfurt am Main, Germany; email: jonas.mosthaf@ecb.europa.eu

Charles O'Donnell
European Central Bank, Frankfurt am Main, Germany; email: charles.odonnell@ecb.europa.eu

Spyros Palligkinis
European Central Bank, Frankfurt am Main, Germany; email: spyros.palligkinis@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from the ECB website, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Occasional Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-4510-3, ISSN 1725-6534, doi:10.2866/965881, QB-AQ-21-001-EN-N