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Large Is Riskier: The Case of European Commercial Banks

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Abstract

Which factors determine the systematic risk of European banks? The issue is very important for regulators and decision-makers in financial markets. This study follows the Beaver, Kettler and Scholes (1970)'s pioneering approach, which estimates true betas of not-financial firms by correcting the observed market betas through the fundamental financial/accounting ratios that better explain the systematic risk. By extending this approach to commercial banks, the fundamental betas of a sample of more than 100 European banks in 2006-2015 period, are empirically estimated. The emerging findings show that size, diversification, derivatives, and TEXAS ratio increase the systematic risk of banks and that the risk weighting of assets, based on Basel framework, does not correctly catch the bank risks (as perceived by the market), since it influences negatively their beta.

This evidence weakens the dominant belief among European supervisory institutions and governments that growing up through M&As is the panacea for European banks.

Keywords: drivers of systematic risk, fundamental beta, European banks, Basel rules

JEL codes: G21, G28

1. Introduction

An in-depth understanding of bank risk is important for a range of financial market participants. It is of interest of regulation and supervisory authorities, who are responsible for maintaining the financial system stability. Furthermore, it is of interest of the financial market operators (banks, investors, etc.), because the most of their decisions are influenced by the determinants of bank risk: it is enough to think of the relevance of estimating a bank's cost of capital, which depends on systematic risk, in order to assess, for example, if bank profitability is adequate (compared to the return requested by the risk borne), or to estimate the cost of capital in M&As or asset management operations (Note 1).

The international literature on bank risk is very wide-ranging. The various strands connect the total risk of a bank (mainly, credit risk and bankruptcy risk) to different categories of determinants, including bank characteristics, regulation policies, industry competition, deposit guarantee framework, etc. Useful indeed, because very concise, is the recent review by Ben Jabra et al. (2017). There are also very ample statistics/studies from European or international supervisory authorities: for example, the ECB studies on financial stability, SREP tools (Supervisory Review and Evaluation Process), the Basel Committee's studies/documents, the EBA (European Banking Authority) risk dashboard, the Global Financial Stability Reports from the IMF (International Monetary Fund), etc. These studies have been re-awakening during the last decade, in the aftermath of the recent financial crisis and the related destabilizing impacts on financial market (Baselga-Pascual et al., 2015).

This study, however, assumes a different perspective, focused on a particular measure of a bank's systematic risk. In fact, the object is to empirically estimate a model which explains the beta of the European commercial bank stocks by means of a set of economic and financial fundamentals, provided by their financial statements. By utilizing a sample of more than 100 European banks, whose main activity is the traditional financial intermediation business, in the 2006-2015 decade, we use the theoretical model of fundamental beta, previously formulated for non-financial firms by the pioneering study of Beaver, Kettler and Scholes (1970) (BKS from now), which seems to be very significant for financial companies for the following reasons:

- Capital Asset Pricing Model (CAPM) is a pricing model that functions well in explaining the returns of bank stocks (Damodaran, 2009);

- the bank stock market is highly influenced by rumors and speculative behaviors which might distort the observed market prices, and therefore the estimated historical betas;
- therefore, given above, if beta is a good measure of a bank's systematic risk, it doesn't seem to be correctly estimated by regressing past market excess returns in function of the corresponding excess returns of the market portfolio proxy, since stock market prices could be biased.

The fundamental beta is, therefore, an alternative measure, which estimates the *true beta* as a function of bank economic and financial fundamentals and cleans up the historical beta from errors.

This study contributes to extend the empirical findings on European banks (Baele et al., 2007; Haq & Heaney, 2012), that appear more limited than those on U.S. banks (Leung et al., 2015; Stiroh 2004 and 2006; Stiroh & Rumble, 2006; Stever, 2007). Moreover, the aim is also to verify the impact of size and business diversification on systematic risk: if, as we expect, both increase the bank's risk, the empirical findings should lead operators and regulators to change their currently dominant attitude in favor of both M&As among banks and a shift of the bank's business towards investment activities, which are riskier, to the disadvantage of traditional lending activity in the real economy, with obvious implications on moral hazard behavior from bankers due to the well-known "*too big to fail*" effect (Note 2).

This study also wants to verify if the Basel coefficients stated for risk weighting bank assets are actually able to measure risk correctly.

2. The Theoretical and Empirical Framework

2.1 Measuring the Systematic Risk: Market Beta vs Fundamental Beta

Given the portfolio diversification theory, the relevant risk (i.e. the risk to be remunerated by market) is the systematic risk, measurable in the modern finance theory from beta, which measures how the excess returns of a single stock or portfolio is sensitive to the variance of the excess returns of a well-diversified portfolio, that is an appropriate proxy of the market risk. Beta (Sharpe 1964; Lintner 1965), therefore, is the coefficient of the time-series linear regression among the past stock excess returns and the corresponding excess returns of the market portfolio proxy.

There are many criticisms about the market measure of beta: *i)* past returns instead of future returns in its estimation; *ii)* bias related to the return frequency adopted in regression; *iii)* the choice of an appropriate *proxy* of market portfolio is a critical aspect, according with Roll (1977); *iv)* betas change over time as far as firms change (Damodaran, 1999); *v)* multi-factor models (Fama & French, 1992 and 1993) undermined the CAPM/beta validity, showing that there are systematic risk components other than beta, in particular the *size-effect* and the *book-to-market-value* premium.

Many studies (BKS, 1970; Bildersee, 1975; Eskew, 1979; Jarvela et al., 2009) affirm that corporate financial statements contain data and information that can be used for measuring risk. The question is: are the risk measures based on accounting data related to risk measures based on market data, in particular to beta? If stock market prices reflect the firm fundamentals, then these fundamentals could be used to explain different betas among stocks. Therefore, it is very relevant to know which fundamentals affect beta more significantly, both to orient decision making in terms of risk implications, and to utilize them for estimating stock/portfolio beta, given the many criticisms that undermine beta estimation based on historical market data.

The fundamental beta approach estimates beta based on identifying the main drivers of systematic risk. This approach was firstly introduced by BKS study in 1970, which oriented many subsequent studies. The study is based upon an analysis of 307 firms listed at the New York Stock Exchange (NYSE) in the period 1947-1965. The nineteen-year period was further divided into two subperiods of ten years (1947-1965) and nine years (1957-1965), respectively. The partitioning of the total time period will permit an analysis of the stationarity of the relationships over time and an examination of the ability of accounting data to forecast into a future period. Firstly, the authors used time series regressions for ex post empirical estimate of systematic risk (stock excess returns versus NYSE index excess returns); a separate regression was computed for each security and for each subperiod: therefore, 307 regressions were computed for each of the two subperiods, resulting in a total of 614. Secondly, BKS identified the relevant accounting variables able to explain systematic risk by analyzing correlations among betas and accounting fundamentals. Finally, BKS utilized the accounting data as instrumental variables in forming estimates of beta in period one that will reduce or eliminate the errors in the observed historical beta. This was directed to compare the ability of accounting risk measures in period one (the fundamental beta) to forecast the market-determined risk measure (historical beta) in period two.

Historical beta (β_H) is an estimate subjected to the error (ω) of *true beta* (β_T), which we cannot observe directly:

$$\beta_H = \beta_T + \omega \tag{1}$$

The instrumental variables approach states that, although the true beta may be directly unobservable, it is linearly related to *n* observable variables, $z_1$through z_n (called instrumental variables):

$$\beta_T = \varphi_0 + \varphi_1 * z_1 + \dots + \varphi_n * z_n \tag{2}$$

where z_i are the accounting fundamentals and φ_i are the true beta's sensitivities to these variables. Analogously, we can estimate from the following cross-section linear regression equation the sensitivities of historical beta (which is observable) to the instrumental variables:

$$\beta_H = c_0 + c_1 * z_1 + \dots + c_n * z_n + \omega \tag{3}$$

The error term ω reflects error in β_H .

Therefore, by removing the error (ω) from β_H we obtain the estimate of true beta, i.e. the fundamental beta β_F.

$$\beta_F = \beta_H - \omega \tag{4}$$

The multiple correlation coefficient in BKS implied an R^2 (a measure of the explaining power of the model) of about 45%. An extremely low R^2 would probably indicate that the wrong instruments were chosen. On the other hand, extremely high correlation would result in a fundamental beta essentially equal to the historical beta, which would defeat the purpose of attempting to remove measurement errors in the last.

Finally, the ability of both β_H and β_F in period one to forecast the market-determined risk measure in period two was analyzed. The following relationship between the *true betas* of the two sub-periods is assumed:

$$\beta_2 = \delta_{10} + \delta_{11} * \beta_1 \text{ where } \delta_{10} = 0 \text{ and } \delta_{11} = 1 \tag{5}$$

Beta is assumed to be stable along the period. BKS empirical findings reveal the consistently superior performance of the instrumental variables approach in forecasting risk measure than the historical beta: the mean of the squared errors as well as the mean of the absolute value of the errors are consistently larger for the naive model (historical beta). The margin of superiority increases at the portfolio level (61 portfolios of 5 securities each): in all cases, the fundamental beta has a larger forecasting ability than historical beta (the mean absolute error is about half). Moreover, the instrumental model had a lower error than the naïve model in the tail areas (operationally defined to be the upper and lower deciles at the individual level and the upper and lower quartiles at the portfolio level) and this is very useful, since they are probably the areas where accurate forecasts are most needed.

However, the approach presents some limits. Firstly, in the cross-section regression, it should be better to use homogeneous firms, for example belonging to the same industry, because it seems reasonable that risk drivers vary across sectors: therefore, the instrumental variables set might be industry specific. A second criticism concerns the flaws of accounting data: Shan et al. (2013) show that the variability of accounting data might depend not only on risk of innate accounting variables (i.e. fundamentals influencing business risk), but be subject to managerial discretions either to signal private (predictive) information or to manipulate earnings opportunistically. The authors further decompose accrual variability into fundamental and discretionary components and examine whether these two components have distinct effects on stock return volatility. Their empirical results show that:

- the conditional variance of accounting data is part of the conditional variance of stock returns; put simply, the uncertainty evident in accounting data is reflected in return fluctuations;
- the positive relationship between accounting data variability and future stock return volatility is dominated by the fundamental portion of accounting data. Hence, it appears that the predictive content of accounting uncertainty is associated with a firm's fundamental uncertainty, rather than any volatile discretionary component, which is more likely to reflect accounting choices, implementation decisions, and managerial opportunism;
- the effect of the discretionary component on future stock return volatility is substantially lower and economically insignificant; this suggests that uncertainty reflected in current-period accounting information contributes to the fluctuation of stock returns, and this is predominantly a reflection of a firm's fundamental uncertainty rather than managerial choices and interventions in the accounting process.

2.2 The Determinants of Beta in Non-Financial Firms

The main drivers of systematic risk emerging from BKS' s study and the related strand are as follows:

- **dividend pay-out** (BKS, 1970; Eskew, 1979; Jarvela et al., 2009), measured as the sum of cash dividends paid out divided by the earnings available for common stockholders. The emerging link is negative: firms with low pay-out ratios are riskier. The belief can be rationalized by the signaling theory, according to which managers have better information about firm than outside investors and therefore can provide information about firm conditions to the market through the dividend policy. As well known in the international literature (Lintner, 1956; Fama & Babiak, 1968; Bharati et al., 1998), firms follow a policy of dividend stabilization (i.e. firms are reluctant to cut back, once a dividend level has been established), and they are averse to paying out more than 100 percent (or x percent) of earnings in any single fiscal period, then firms with greater volatility in earnings will pay out a lower percentage of expected earnings. Thus, the pay-out ratio can be viewed as a surrogate for management's perception of the uncertainty associated with the firm's earnings;

- **growth** (BKS, 1970; Bildersee, 1975; Eskew, 1979), measured as natural logarithm of the ratio of the terminal asset size divided by the initial asset size. The expected relationship is positive: in a competitive economy the excessive earnings opportunities of any firm will erode as other firms enter, then it can be argued that these excessive earnings streams are more uncertain (i.e. volatile) than the "normal" earnings stream of the firm. In addition, growth is negatively associated with pay-out;

- **leverage**: as debt is introduced, the earnings stream of the common stockholders becomes more volatile (Modigliani & Miller, 1958; Clere, 2019). According to the second proposition of Modigliani and Miller theory, the levered cost of capital of a firm increases as far as the market value of debt divided market equity increases. According with CAPM, the relationship between returns lead to the corresponding relation between betas:

$$\beta_e = \beta_u + \frac{D}{E} * (\beta_u - \beta_d) \tag{6}$$

- **liquidity** measured by current ratio (current assets divided current liabilities). We expect a negative link with beta: liquid assets or current assets have a less volatile return than noncurrent assets. Larger the liquidity, less probable the bankruptcy. However, liquidity in excess is disadvantageous as far as taxes are concerned and could generate agency costs: in fact, entrenched managers can use large free cash flows inefficiently;

- **size** measured by the natural logarithm of total assets (Note 3): it is widely believed that larger firms are less risky than smaller firms. In terms of default risk, the evidence indicates that the frequency of failure is lower for the large size classes. Moreover, larger firms are more diversified and if individual asset returns are less than perfectly correlated, larger firms will have lower variance of rate of return than smaller firms. In terms of portfolio theory, however, as long as the investor can diversify out of the individualistic risk, he is indifferent to whether an individual firm is an efficient portfolio in and of itself. Many studies (Gu and Kim 1998; Titman and Wessels 1988) show that the systematic risk of larger firms is less than the smaller since they are able to better face the adverse economic changes. In addition, larger firms can realize scale economies and therefore reduce the incidence of direct bankruptcy costs on company value (Ang et al. 1982; Warner 1977). Finally, Fama and French (1992 and 1993), found that market returns remunerate a "*small minus big*" premium for systematic risk. We expect a negative impact of size on beta;

- **variability in earnings**, measured (BKS, 1970; Bildersee, 1975; Eskew, 1979; Jarvela et al., 2009) by the standard deviation of an earnings-price ratio (i.e. income available for common stockholders to market value of common stock outstanding): $\sigma_{E/P} = \sqrt{\frac{1}{T}\left[\ \sum_{t=1}^{T} \frac{E_t}{P_{t-1}} - \left(\ \frac{\bar{E}}{\bar{P}}\ \right)^2\right]}$. This variable affects negatively beta;

- **accounting beta**: it can be derived in a similar manner to the market beta, that is from a time series regression with the firm's earnings-price ratio as the dependent variable and some economy-wide average of earnings-price as the independent variable. The expected link is positive, but it for each security will be estimated on a small number of observations, which implies that estimates will be subject to a large amount of sampling error (earnings are available only yearly).

The cited empirical studies obtain statistically significant results, consistent with the expected signs.

Relevant is the Jarvela et al. (2009)' study, which aims at verifying if BKS approach was still valid in recent years: they obtain consistent results, except for some variables: in particular, the dividend pay-out does not explain beta for larger companies and earnings volatility has a very weak impact on beta, although statically significant.

2.3 The Drivers of Bank Beta

Many recent studies focus on identifying drivers of bank systematic risk. We will analyze the main fundamentals emerging from these studies.

Firstly, **diversification**. Banks are allowed to diversify functionally. From a regulatory perspective, they can combine commercial banking, securities, insurance and other financial activities in a conglomerate organizational form. The European regulatory framework allows a more diversification degree than U.S. banks, longer regulatorily constrained. Baele et al. (2007) discuss costs and benefits of diversification on profitability and risk. Firstly, the formation of financial conglomerates would be beneficial if there are positive cost and/or revenue effects from combining various financial services activities. Similarly, the operating costs of financial conglomerates would be lower in comparison to specialized banks if integration leads to economies of scope. Secondly, banks possess information from their lending relations that may facilitate the efficient provision of other financial services, including securities underwriting or insurance. Similarly, information acquired through securities or insurance underwriting can improve loan origination and credit risk management. Thus, financial conglomerates could enjoy economies of information that boost performance and market prices. Thirdly, the potential for functional diversification may improve corporate governance through the working of the takeover market. When cross-activity mergers are allowed, managers of financial firms incur stronger monitoring by the takeover market. From the risk perspective, standard portfolio theory predicts that the combined cash flows from non-correlated revenue sources should be more stable than the constituent parts. However, diversification can simply be pursued by investors at individual portfolio level.

On the cost side, agency costs may arise due to the complexity of the conglomerate organization. Diversification of activities in a conglomerate structure could intensify agency problems, between insiders and outsiders, but also between the divisions of the conglomerate and between the conglomerate firm and its customers in the form of conflicts of interest. In addition, regulatory costs associated with multiple supervision can be invoked.

If theoretically it is unclear whether or not the potential benefits of functional diversification are larger than the costs, many studies (Stiroh & Rumble, 2006; Stiroh, 2004 and 2006; DeYoung & Roland, 2001; Baele et al., 2007; Demirguc-Kunt & Huizinga, 2010) empirically show significant positive links between non-interest income (non-interest income captures all income streams generated by a broad array of financial services provided by functionally diversified banks) and volatility of market returns or accounting earnings. Diversification generates an increased exposure to non-interest activities, which are much more volatile than interest-generating activities. Diversification allows financial conglomerates to sell various financial products/services to the same customers: this strategy could increase revenues, but it also increases bank vulnerability to the same kind of risk (therefore, a positive impact on systematic risk). The above empirical findings show that more diversified banks have a higher exposure to changes in market sentiment or economy-wide shocks. As far as the idiosyncratic risk is concerned, evidence from European banks reveals that an increasing reliance on non-interest income decreases a bank's idiosyncratic volatility; however, this relationship is nonlinear. Once a bank becomes too exposed to non-traditional banking activities, its bank-specific risk increases. The impact on bank total risk of diversification would be positive. U.S. bank studies (Stiroh, 2006) reveal a linear and positive linkage between diversification and risk, both systematic and total.

Size is another determinant of risk. Differently from non-financial firms, banks' equity betas are positively related to size. Small banks appear to make safer loans than large banks. As a result, individual loans at small banks exhibit less sensitivity to market movements (and other risk factors) than large bank loans. However, due to small banks' inability to diversify, the total equity volatility of large and small banks is the same (given the high regulatory degree in this industry). This evidence depends partially on the effect of diversification: banks grow through diversifying their activities. Stever (2007) shows, in addition, that small banks may lend to similar sectors and asset types as large banks, but they make loans with lower credit risk. They may require more collateral per loan or have superior information on borrower risk (since small banks have both a smaller number of loans and fewer groups of firms to which they can lend, they can pursue a better monitoring of their borrowers). The dataset in this study has over 300 U.S. publicly traded banks from 1986 to 2003. Stever shows that the loan charge-off and delinquency rates at large banks are higher than small banks. Large banks lend more aggressively and extend more credit than small banks, and therefore, as a consequence, on average their loans have a lower success rate (Note 4).

Haq & Heaney (2012) observe that the regulatory protection of larger banks could result in large banks becoming "too big to fail" and this could increase the incentive for large banks to undertake riskier activities (i.e. a moral hazard behavior), particularly the riskier non-interest generating activities. Large banks could also be more sensitive to general market movements than small banks leading to a positive relation between bank systematic risk and size. Their study, conducted on a sample of 117 European commercial banks (from 15 European countries) in the 1996-2010 period, highlights:

- a positive statistically significant linkage between size and systematic risk;
- a negative statistically significant linkage between size and idiosyncratic risk;

- a positive statistically significant linkage between size and total risk.

These results are substantially confirmed in Baele et al. (2007) study, regarding European banks too. As far as studies on U.S. banks are concerned (Stiroh, 2006 and Leung et al., 2015), the size impact is positive on beta, but negative on total risk: it means that, differently from European banks, in U.S. banks the negative impact of size on idiosyncratic risk overcomes the positive one on beta.

Other fundamentals of beta are the following:

1. **capital adequacy** CET1, measured as Tier 1 (i.e. "core capital" which consists primarily of common stock, reserves and retained earnings), divided by risk-weighted assets (RWA), based on Basel Accord standard weights, or internal ratings (IRB=*Internal Rating Based*), when banks are authorized to adopt them. It is the basis par-excellence of the micro-prudential supervisory framework of Basel Committee. Haq & Heaney (2012) assume a negative relationship between CET1 and risk (systematic, idiosyncratic and total). Banks generally maintain a capital buffer to absorb losses that arise from their loan portfolio, adjusting the buffer as the risk of their loan portfolio changes over time. Moreover, regulators require banks to hold capital to protect them against the cost of financial distress, agency problems and to curtail the risk shifting benefit arising from deposit insurance. However, the impact of capital regulation on bank risk is ambiguous. For example, in an agency problem framework, higher capital standards help to reduce the risk of the bank's assets; however, with the bank issuance of equity to meet the new standards, bank insider effort decreases since their equity stake decreases. Moreover, bank capital regulation suggesting higher capital levels may induce banks to increase asset portfolio risk and the probability of default. They propose a 'U-shaped' relation between bank capital and bank risk, thus reconciling the two opposing views on the effect of bank capital on bank risk. The authors argue that the turning point occurs when banks start to take on more profitable, albeit potentially riskier, investments, either because the probability of bank default is very remote or because, in the event of bankruptcy, the bank can shift the cost of default onto the deposit insurance agency (moral hazard problem). Their empirical results support the nonlinear linkage of CET1 with beta. In Leung et al. (2015) study on U.S. banks, CET1 decreases the total and idiosyncratic risk, but not the systematic one (the nonlinear relationship is not tested, however);
2. **off-balance sheet items** (bank guarantees attached to commercial letters of credit, loan commitments and stand-by letters of credit, derivative obligations, etc.). Greater levels of regulation and increased competition have resulted in banks developing non-traditional activities which, while not appearing on the balance sheet, do create contingent assets and liabilities, which are difficult for investors and regulators to be assessed in terms of risk implications. The theoretical literature assumes that they increase bank risk and empirical findings prove this impact;
3. **dividend pay-out,** whose impact on beta is assumed negative, as in non-financial firms (see section 2.2);
4. **incidence of non-performing loans:** Leung et al. (2015) affirm that banks with stronger risk control had lower non-performing loans. Therefore, the determinant serves as a *proxy* of bank efficiency in risk monitoring. Empirical evidence supports the expected positive linkage only with idiosyncratic and total risk, but not with systematic one;
5. **operational inefficiency**, in terms of cost-to-income ratio (i.e. the ratio of all operating expenses as a fraction of the sum of net interest and non-interest revenues) (Baele et al., 2007). Better performing banks in terms of superior technology and more skilled management (Baselga-Pascual et al., 2015) are perceived less risky by market; in addition, operational efficiency should protect banks from unexpected volatility of profits. No particular effect, however, is expected on systematic risk and empirical evidence supported this assumption.

3. The Empirical Test on a Sample of European Commercial Banks

3.1 Hypotheses Tested

We empirically tested the following hypotheses on a sample of European commercial banks.

H1. Size increases beta.

Large banks lend more aggressively and extend more credit than small banks, and therefore, as a consequence, on average their loans have a lower success rate.

In addition, banks grow through diversifying their activities and undertaking riskier activities. This behavior favors moral hazard attitude: large banks become "too big to fail". Moreover, banks, as they become larger through diversification, are more interconnected to the whole financial system.

H2. Diversification increases beta

Diversification generates an increased exposure to non-interest activities (financial investments, trading, insurance, etc.), which are much more volatile than interest-generating (more traditional) activities.

H3. Systematic risk decreases with increasing dividend pay-out

According with the signaling theory (Lintner, 1956; Fama & Babiak, 1968; Bharati et al., 1998), if managers have better information about firm than outside investors, they can provide information about firm conditions to the market through the dividend policy. Therefore, pay-out ratio can be viewed as a surrogate for management's perception of the uncertainty associated with the firm's earnings: higher pay-out indicates higher expected earnings and less bankruptcy risk.

H4. RWA (divided by total assets) increases beta

RWA (risk-weighted assets on total assets) measure assets weighted by the Basel II-III coefficients: it represents a very important indicator of bank capital adequacy (since supervisory authorities base the regulatory capital requirements by using this figure). Therefore, this ratio should sum up "in a nutshell" the most important risk drivers for a certain financial activity. Risk-weighting coefficients (fixed by Basel Committee rules), if appropriately measured, should increase with increasing risk of assets. However, the expected could be of the opposite sign if the risk-weighting framework was biased (as emerging from recent studies in Europe). In fact, Basel rules could fail in measuring risk and erroneously direct the bankers' decisions. Some studies show that the risk-weighting coefficients penalize exposures to corporates (non-financial firms) in comparison with exposures to governments, banks and central bank institutions, stating for the former risk-weighting coefficients higher than the latter, with the same creditworthiness. It seems an inexplicable choice, since it underestimates the enhancing systemic effect that a bank or government defaults/bankruptcies generate if compared to similar events concerning non-financial firms. This distortion, highlighted by many studies (Angelini, 2016), has been confirmed by the following counter-intuitive linkages of RWA/total assets ratio emerging in Mediobanca-Ricerche & Studi Annual Report on international banks (Mediobanca-R&S, 2014; Barbaresco, 2015): positive with loans on asset incidence, on the one hand, and negative with derivatives incidence on tangible net worth, on the other. These findings show that the Basel risk-weighting coefficients penalize customer loans in comparison with other assets (including derivatives). Furthermore, the Basel II-III framework boosts internal rating (i.e. measured by banks) in comparison to the standard rating system, assigned by rating agencies. Regulatory capital requirements could be less tightening in the former. It is important to consider that a self-regulation mechanism (by means of internal ratings) or a power delegation to rating agencies (by means of standard ratings) are introduced in this way. They represent factors of further risk, which depends on suitability of the utilized models by delegated parties and related fiduciary relationships in a context already weakly based on reliance; moreover, they are statistical models very complex, for which effective monitoring/validation by regulators is likely to be very difficult. Internal ratings would undervalue bank risk, as recent studies by supervisory authorities show (Behn et al., 2016; Cannata et al., 2012).

H5. Capital adequacy lessens systematic risk

According with Haq & Heaney (2012), a higher Tier1 functions as a capital buffer for absorbing potential future losses and reducing distress costs. In addition, higher net worth means less agency costs. Differently from previous studies, capital adequacy is not measured here by using CET1. Firstly, since CET1 is highly correlated with RWA (Pearson coefficient is -38%); secondly, because the above discussed distortion in calculating RWA could also bias CET1. Here, we will use TEXAS ratio, measured as net NPL on tangible equity. Since the sample in this study includes only commercial banks (see infra § 3.2), whose dominant business is credit intermediation: *i)* loans are the most part of assets; *ii)* credit risk is the main component of total risk; *iii)* therefore, capital adequacy might be better measured by how equity capital faces up to shortfalls deriving from NPL write-down. In addition, among the determinants of beta (see below hypothesis 9) leverage is included (since it is calculated by using Tier1, it can make up for the lack of CET1). A higher TEXAS ratio increases a bank's systemic risk. Tangible equity capital excludes intangibles, which are assets of uncertain valuation and differ among banks, if they grow internally rather than through mergers (goodwill).

H6. Operational inefficiency does not affect systematic risk

According with Baele et al. (2007), better performing banks in terms of superior technology and more skilled management (Baselga-Pascual et al., 2015) will be perceived less risky by the market, but no impact is expected on systematic risk (inefficiency increases bank idiosyncratic risk).

H7. Opaque assets (i.e. assets of subjective and doubtful value) increase beta

Bank investment in opaque assets has a stronger impact on bank risk than transparent assets. Asset opacity is not appreciated by the market. We assume the intangibles are opaque because their value written in the balance sheet is discretionary. In fact, their value is often calculated by means of models based on subjective estimations, not directly verifiable.

H8. Derivatives increase beta

Derivate assets have high risk (amplified in comparison to underlying assets), and they are opaque in balance sheet value. Derivatives are available for a few banks only (this explains a smaller sample than original). Obviously, derivatives are physiologically used for hedging bank portfolio, but it is impossible to distinguish among hedging and speculative uses.

H9. Leverage amplifies systematic risk

Leverage (total assets on Tier1) showed to be more effective than more common indicators (for example, CET1) in forecasting bank distress in the recent crisis (BCBS 2014). In fact, Basel III re-introduces it among indicators to be controlled. However, bank leverage has not the same meaning than in non-financial firms. Many studies on fundamental beta of banks do not include leverage among regressors, or, when they do, statistically non-significant coefficients are obtained: see, for example, Haq & Heaney (2012) and Leung et al. (2015). Moreover, leverage might affect idiosyncratic risk more than systematic one: if bank monitors total risk, the leverage impact on systematic risk could be of opposite sign than assumed (higher systematic risk can induce strategies that don't enhance leverage). In addition, if leverage affects the returns, its impact on beta might be distorted by the beta-returns relationship; or, if banks become larger through increasing leverage, leverage effect on beta can be absorbed by size impact (Bhagat et al., 2015) (Note 5).

3.2 The Sample

The dataset consists of 149 listed banks from 17 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, The Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the The United Kingdom) in 2006-2015 period (it is a balanced sample: 10-year observations for each bank): a sample of 1490 bank-year observations in total. From the universe of commercial listed banks (data provider is Thompson Reuter Eikon - Datastream Equities and Worldscope Fundamentals), we selected only banks with the first SICcode (i.e. the dominant business by revenues) equal to 6029 (*Commercial Banks, NEC*) or 6022 (*State Commercial Banks*) or 6035 (*Savings Institutions, Federally Chartered*), institutions that offer similar commercial banking services (in detail, 1400 bank-year observations with the first code, 20 for the second e 70 with the third).

Table 1. Sample by country

Country	*Sample bank number*	*Datastream bank number*
Austria	6	7
Belgium	2	8
Denmark	21	22
Finland	2	5
France	18	18
Germany	9	15
Greece	5	6
Ireland	2	3
Italy	16	16
Netherlands	2	3
Norway	20	23
Poland	10	15
Portugal	2	2
Spain	6	8
Sweden	4	4
Switzerland	17	27
United Kingdom	7	9
Total	149	191

However, the sample homogeneity in terms of dominant business does not exclude other business lines in bank activity (Note 6).

Further details on the sample are provided in Tables 1, 2 and 3.

Table 2. Sample by size

	Total assets (billion euros)	*Number of employees*
mean	263.5	17,999
median	23.5	1,838
5th percentile	2.0	62
95th percentile	1,717	119,530
coefficient of variation	2.62	2.35
interquartile range/median	4.27	6.52

Table 3. Sample by incidence of credit intermediation activity

	loans on total assets	*deposits on total liabilities*
mean (%)	72.2	52.0
median (%)	75.6	52.7
5th percentile (%)	37.9	23.2
95th percentile (%)	90.8	80.6
coefficient of variation	0.23	0.34
interquartile range/median	0.28	0.52

The sample is very variegated in terms of size, as dispersion coefficients show (see Table 2). On average, assets amount to 263 billion euros, and the half of sample has assets lower than 23.5 billion. Even though sample includes only listed banks, there is not lack of smaller ones: the 5% of distribution has assets less than 2 billion and employees less than 62.

Table 3 shows the weight on assets of credit intermediation activity: the sample is very homogeneous in terms of dominant business, as two dispersion coefficients show. The traditional business of collection of savings and lending is dominant, consistently with their profile of commercial banks: if we exclude the distribution tails, loans to customers are at least 40% of assets and deposits about 25%; in at least a half of banks, 75% and over 50%, respectively.

3.3 Variables, Tested Model and Statistical Methodology

Datastream beta is calculated yearly, by using time series regressions of 60 monthly logarithmic returns (in a 5-year period) of each bank with respect to local index returns (e.g. of the corresponding listed country stock market) (if multi-listed stocks, the first listed market is considered). Table 4 shows the determinants of beta, highlighting the related methods of calculation.

In addition to the hypotheses discussed in section 3.1, some interactions among variables are considered:

- between RWA intensity and dummy rating, respectively *dummy_IRB* (equal to 1 when bank assets are higher than 50 billion euros) and *dummy_STD* (equal to 1 when assets do not overcome 50 billion). This dummy should distinguish banks that utilize internal ratings from banks that adopt standard ratings. This is a proxy, that is based on size to distinguish rating system for calculating RWA, because effective data about adoption are not available (the size threshold is derived by a limited sample of banks for which the adopted rating system was known). We want to verify if the counter-intuitive relationship between beta and RWA might depend on adoption of one or the other risk-weighting system;

- between PAYOUT and TEXAS ratio, on the one hand, and dummy_CRISIS, on the other, to verify if the impacts would have differed during the years of the recent financial crisis (2008-2010). For example, we can assume that, according with signaling theory, dividend distribution can affect beta more strongly, since it is a more credible signal during crisis, or alternatively, the impact of NPLs on risk could be enhanced.

We include country dummies (Italy as reference basis), as fixed effects, and the variable GDP_index (index number of GDP, per country-year) which serves as proxy of both time effect and country economic scenario.

The tested model is the following:

$$\beta_{i,j,t} = \alpha + \varphi \times \left[DETERMINANTS_{i,j,t}\right] + \varphi_{RWA} \times dummy\_rating_{i,j,t} \times RWA_{i,j,t} + \varphi_{TEXAS} \times dummy\_crisis_{i,t} \times TEXAS_{i,j,t} + \varphi_{PAYOUT} \times dummy\_crisis_{i,t} \times PAYOUT_{i,j,t} + \alpha_P \times COUNTRY_j + \alpha_{P,T} \times GDP\_index_{j,t} + u_{i,j,t} \quad (7)$$

Table 4. Determinants of beta

determinants	*symbol*	*calculation*
size	SIZE	ln (total assets)
diversification	DIV	noninterest revenues/total revenues
dividend pay-out	PAYOUT	paid dividends/net income
operational inefficiency	INEFFICIENCY	(operating costs – provisions for credit losses)/total revenues
opacity of assets	OPACITY	intangibles/total assets
derivatives on total assets	DERIVATIVES	derivatives/total assets
risk-weighted assets intensity	RWA	risk-weighted assets/total assets
leverage	LEVERAGE	total assets/TIER 1
texas ratio	TEXAS	non-performing loans (net of related provisions) /tangible equity capital
proxy internal ratings	dummy IRB	= 1 if total assets > 50 md
proxy standard ratings	dummy_STD	= 1 if total assets ≤ 50 md
dummy crisis years	dummy_CRISIS	= 1 for years 2008, 2009 and 2010
GDP index number	GDP_index	basis 2005, nominal values
country dummies	DCOUNTRY_Austria…DCOUNTRY_UK	= 1 if belonging to country

α and φ parameters are, respectively, the intercept and the coefficient vector of k determinants of beta, $[DETERMINANTS]$ is the matrix of the assumed determinants of bank systematic risk. $u_{i,j,t}$ is the term of error. The model was tested using *pooled* OLS (Note 7) (from GRETL package): error estimation (heteroskedastic and auto-correlated in series) uses HAC methodology (*Heteroskedasticity and Autocorrelation Consistent*) and therefore can be considered robust (Arellano, 2003).

3.4 Results

3.4.1 Descriptive Statistics

Table 5 summarizes the descriptive statistics of beta, Table 6 the correlation matrix and Table 7 the descriptive statistics of beta determinants. All are referred to the whole sample. Beta variance seems to be appropriate (as shown by two dispersion indicators) for estimating the effects of determinants.

Preliminary findings emerge from the correlation matrix, that confirm some formulated hypotheses: positive impact on beta of size, diversification, derivatives, asset opacity and NPL weight. Some evidence confirms also the suspected distortions in risk-weighting of assets, based on Basel framework. In fact, we can observe that RWA is negatively correlated to beta as well as derivatives incidence: both correlation signs appear counter-intuitive.

We can see, furthermore, that large banks have more derivatives and diversification causes more opacity of assets (diversification is likely to induce acquisitions with goodwill). In addition, dividend pay-out is constrained by incidence of both NPLs (negative correlation of PAYOUT with TEXAS) and operational costs (negative correlation with INEFFICIENCY). We cannot make a trend analysis on determinant descriptive statistics, since data of some years are not available and, therefore, sample mix is not homogeneous over the years.

3.4.2 Regression Results

Table 8 sums up the regression results. We tested different models, including various groups of determinants. The final sample (due to data availability) includes 112 banks (the 5 models in the table are comparable, because they use the same observations). Results reveal that size, diversification, derivatives and NPL incidence increase a bank's systematic risk, confirming hypotheses 1, 2,5 and 8. Dividend pay-out, on the contrary, decreases beta (according to hypothesis 3): the signal seems to be stronger in crisis years; in fact, in model 2, the coefficient of interaction variable dummy_CRISIS × PAYOUT is statistically significant. Consistently with our tested hypotheses and international empirical evidence, beta is not affected by operational inefficiency. Asset opacity never shows a statistically significant impact on beta, although the sign of relationship is as expected. Therefore, hypothesis 7 is not verified. However, the reason could be twofold: on the one hand, correlation matrix (Table 6) shows a strong positive relationship of opacity with size and diversification, proving that these two determinants absorb the opacity effect on beta; on the other hand, the used proxy is weak, since *intangibles* are too generical and non-analytical category, since they can include many different components (detailed data are not available).

In contrast with hypothesis 9, leverage does not influence beta (see model 5), even when the logarithmic transformation is used – ln (LEVERAGE) – to linearize the relationship; however, the linkage results significant in models 1 to 4, but the sign is opposite to what is expected: we can explain this evidence highlighting that leverage affects a bank's idiosyncratic risk and, therefore, if a bank monitors its total risk, when beta increases, the bank also reduces its total risk by means of leverage; the linkage, therefore, could be mediated by a third omitted variable and then it is of opposite sign (and reverse causal link). In addition, as the correlation matrix shows (Table 6), leverage is positively correlated to size and therefore, its impact on beta could be absorbed by the latter.

In addition, we can see (by comparing model 3 to 1 as well as model 5 to 4) that the impact of leverage on systematic risk is likely to be absorbed by the country effect: in fact, when country dummies are introduced, the coefficient of leverage becomes less significant; statistical data from ECB (ECB, 2019) confirm a country characterization of leverage, and this fixed effect (i.e. structural effect), time-invariant, would be stronger in the model in comparison with time-varying values of leverage. As discussed above, bank leverage does not have the same meaning than in non-financial firms. Many studies on the fundamental beta of banks do not include leverage among regressors, or, when they do, statistically non-significant coefficients are obtained: see, for example, Haq & Heaney (2012) and Leung et al. (2015).

Furthermore, the relationship between leverage and beta could be biased by the connection of both with the market returns of bank stocks. Demirguc-Kunt et al. (2013) found a negative impact of leverage on bank stock returns in larger banks, and therefore, since beta positively linked to returns according to CAPM, the negative relationship between leverage and beta might be a derived result.

Table 5. Descriptive statistics of beta

mean	0.77
median	0.68
5^{th} percentile	0.04
95^{th} percentile	1.89
coefficient of variation	0.80
interquartile range/median	1.38

The impact of RWA intensity on beta is counter-intuitively negative, which means that banks perceived by the market as systematically riskier have an RWA/total assets ratio lower and, conversely, banks with higher RWA intensity are perceived as less risky. This evidence confirms distortions of the Basel risk-weighting framework, already discussed. When we distinguish by kind of ratings adopted (models 2 and 5), bias seems larger for banks adopting standard system: in fact, the negative coefficient of the interaction variable dummy_STD × RWA is larger and more statistically significant.

Table 6. Matrix of correlations

	BETA	SIZE	DIV	PAYOUT	INEFFICIENCY	OPACITY	RWA	DERIVATIVES	TEXAS	LEVERAGE
BETA	1	.618**	.173**	-.199**	.171**	.339**	-.372**	.300**	.217**	-0.043
SIZE		1	.068**	.080**	.056*	.249**	-.430**	.337**	0.015	.156**
DIV			1	.060*	0.046	.337**	-.214**	.081**	0.034	-.266**
PAYOUT				1	-.201**	0.033	-.139**	-.096**	-.230**	.177**
INEFFICIENCY					1	.083**	-.233**	.075*	.159**	.203**
OPACITY						1	-.123**	.083**	.101**	-.126**
RWA							1	-.242**	-0.024	-.152**
DERIVATIVES								1	-0.05	.060*
TEXAS									1	.242**
LEVERAGE										1

** sign = 0.01 (two tails) * sign = 0.05 (two tails).

Table 7. Descriptive statistics of beta determinants

	DIV	PAYOUT	INEFFICIENCY	OPACITY	DERIVATIVES (%)	RWA	LEVERAGE	TEXAS	dummy IRB
mean	0.28	0.30	0.78	0.005	1.90	0.57	9.92	0.62	0.36
median	0.26	0.29	0.77	0.002	0.51	0.57	7.99	0.30	0.00
5th percentile	0.08	0.00	0.61	0.000	0.00	0.22	2.02	0.03	0.00
95th percentile	0.57	0.81	0.95	0.025	7.19	0.88	23.5	2.05	1.00
coefficient variation	0.53	0.84	0.15	1.69	2.57	0.41	1.04	1.82	1.33
interquartile range/median	0.57	1.64	0.16	3.12	2.74	0.44	0.70	1.74	

The variable GDP_index, in regressions where country fixed effects are omitted, negatively affects bank beta: in growing economies, market risk is lower (as previous empirical findings confirm) (Note 8). However, its impact is absorbed by country fixed effects; the latter show (in comparison to Italy, used as benchmark) a lower beta, on average, in North Europe countries (Finland and Norway) and in Switzerland, and a higher beta in Belgium, Greece, Ireland, Poland and Portugal (i.e. more volatile countries): significant coefficients of country dummies must be interpreted as corrective of model intercept, which holds for Italian banks (omitted dummy) and for countries with insignificant coefficients of the respective country dummies. The apparently weak relevance of country dummies (8 among 16) might seem a failure of the explanatory model, meaning that economic and political features of country are only weakly relevant in explaining beta. However, we should consider the following points: *i)* sample countries are all members of EU (all 28 member states), with the exception of Switzerland. Therefore, if we consider the global nature of financial systems, these countries are relatively homogeneous from the perspective of beta; *ii)* betas in Datastream are calculated through the well-known time-series regressions among returns of bank stocks and returns of corresponding local market indices; in detail, beta is not an absolute measure of systematic risk, but rather a relative one, i.e. the stock return sensibility to market index of country whom banks belong to: therefore, it could be theoretically neutral with respect to geographical differences among sample observations. Indeed, the country economic and financial characteristics do affect returns and volatility of bank stocks, as well as of the other shares included in the market index, but not necessarily (or in a limited manner, anyway) the structural relationship between true beta and bank fundamentals; *iii)* if we analyze the residual errors of the most complete model 5, we do not observe systematically higher errors in some countries in comparison to others, in particular not for Switzerland or the United Kingdom, which are the potentially less homogeneous countries in our sample.

The model 5 shows a good explanatory power: it explains more than two thirds of beta variance (both longitudinal and cross-sectional). Model 5 was also tested including among regressors the interaction effect of years with the determinants potentially more influenced by regulation, in order to catch the impact related to changes in regulatory framework over the years. Specifically, we considered the interaction effects between year dummies and TEXAS ratio, RWA intensity and LEVERAGE, verifying if there were some significant coefficients. The empirical findings (omitted for brevity) do not show any statistically significant effect.

3.4.3 Endogeneity of Leverage

We verified, by means of the Hausman test, that the leverage variable is endogenous. Therefore, we tested the model presented in Table 9, using the Two-Stage Least Squares (TSLS) regression, by utilizing as an instrument of leverage the diversification variable, selected as a strong instrument. We can see that the signs of the most important links are confirmed (albeit some of them are no longer statistically significant), the impact of the exogeneous leverage on beta is no longer significant (therefore, the negative relationship was causally reversed, due to the effect of idiosyncratic risk, discussed above), and we use the incidence of loans to customers on total assets as a proxy of non-diversification: the negative relationship confirms that the market perceives the banks more focused on intermediation activity (i.e. less diversified) less systematically risky.

The tests confirm the consistency of OLS estimations and the effectiveness of the used instrument.

Table 8. Regression results (pooled OLS)

	MODEL 1		MODEL 2		MODEL 3		MODEL 4		MODEL 5	
	coefficient		*coefficient*		*coefficient*		*coefficient*		*coefficient*	
constant	–0.674704		0.0236626		–1.62594	***	–0.357558		–1.30935	**
SIZE	0.153253	***	0.1104	***	0.136333	***	0.167542	***	0.125416	***
DIV	0.457187		0.551611	*	0.727826	***	0.30486		0.741111	***
PAYOUT	–0.529938	***	–0.423695	***	–0.251153	***	–0.510581	***	–0.237620	***
INEFFICIENCY	0.032376		0.179364		0.0236334		0.261173		0.049607	
OPACITY	4.34145		309.878		5.18250		1.5754		4.64789	
RWA	–0.329487	**			–0.344415	**	–0.476150	***		
TEXAS	0.130673	***	0.117336	***	0.09144	***	0.133557	***	0.091237	***
DERIVATIVES	0.012236	*	0.0137032	**	0.01495	**	0.0121203	**	0.014859	**
LEVERAGE	–0.00501	**	–0.005500	**	–0.00243	*				
GDP_index	–0.009067	***	–0.009689	***	0.0005646		–0.008995	***	0.000218	
dummy_IRB*RWA			–0.132633						–0.320366	*
dummy_STD*RWA			–0.515560	**					–0.407789	**
dummy_CRISIS*PAYOUT			–0.188305	**					–0.058716	
dummy_CRISIS*TEXAS			0.0369362						0.012436	
DCOUNTRY_Austria					0.050076				0.0624145	
DCOUNTRY_Belgium					0.78158	***			0.800342	***
DCOUNTRY_Denmark					–0.154755				–0.140595	
DCOUNTRY_Finland					–0.495281	***			–0.491875	***
DCOUNTRY_France					–0.133565				–0.105568	
DCOUNTRY_Germany					–0.151470				–0.122210	
DCOUNTRY_Greece					0.361257	***			0.357091	***
DCOUNTRY_Ireland					1.48462	***			1.47753	***
DCOUNTRY_Netherlands					–0.111722				–0.088375	
DCOUNTRY_Norway					–0.294759	***			–0.269803	**
DCOUNTRY_Poland					0.17217	*			0.172561	*
DCOUNTRY_Portugal					0.323187	***			0.346641	***
DCOUNTRY_Spain					–0.014855				–0.01036	
DCOUNTRY_Sweden					–0.192124				–0.160551	
DCOUNTRY_Switzerland					–0.305591	**			–0.266471	*
DCOUNTRY_UK					0.120591				0.140141	
ln(LEVERAGE)							–0.23572	***	–0.06078	
adjusted R-squared	0.4994		0.5149		0.6833		0.5181		0.6831	
*** sign=0.01 ** sign=0.05 * sign=0.10			DPAESE_Italy	basis omitted						

Table 9. TSLS regression results

	coefficient
const	0.7999
SIZE	0.1483***
PAYOUT	-0.4778***
INEFFICIENCY	0.6307
OPACITY	-3.5077
TEXAS	0.1321***
DERIVATIVES	0.9999
ln (LEVERAGE)	-0.4451
GDP_index	-0.0077
CUSTOMER LOANS	-06658*
dummy_IRB × RWA	-0.3863
dummy_STD × RWA	-06410**
adjusted R-squared	0.4871
Hausman test	
chi-squared	0.9395
p-value	0.3324
weak instruments test	
F-statistic (first stage)	30.8932

*** sign=0.01 ** sign=0.05 * sign=0.10; robust std errors (HAC).

ln (LEVERAGE) = endogenous variable DIVERSIFICATION = instrument.

4. Preliminary Conclusions

From the empirical test on a sample of more than 100 European commercial banks in 2006-2015 period, size and diversification of assets (which increases with increasing size) result to increase a bank's systematic risk.

This empirical evidence should suggest that regulators (both European and domestic) correct their current orientation in favor of mergers and acquisitions among banks as a panacea for all the evils of the banking system, reasoning that concentration increases system stability (Venanzi, 2018). As shown by many studies, larger size incentives moral hazard behavior of bank managers, related to the *too big to fail* effect. In addition, banking system consolidation creates much interdependence among larger and more complex financial institutions. Managers are encouraged to undertake riskier activities (that could generate more profits), relying on government protection.

Larger size, in addition, generates the following consequences: *i)* makes more complex bank activities and therefore more difficult to assess and monitor risk exposition, from managers/internal controllers as well as supervisory authorities; *ii)* improves interest conflicts of the banking system, since the most of them depend on the presence within the same institution of many and various activities, from commercial (deposit collection and customer lending), under government safeguard, to riskier ones like asset management and proprietary trading (Walter, 2004). Bigger size generally causes a business mix that is more oriented to activities different from traditional credit intermediation (trading, for example), increasing riskier non-interest revenues; from this study we obtain that diversification positively affects (in a statistically significant manner) a bank's systematic risk. ECB 2018 Annual Report (ECB, 2018) shows that the group of less risky banks (based on SREP classification) among the 119 global systemically important banks (supervised directly) have a higher weight of customer loans on total assets (64% versus 58%) and a lower of investments (14.5% vs 18%) and derivatives (6.7% vs 8.9%) in comparison with the group of banks with medium or high risk.

Finally, from this study the failure of Basel coefficients of asset risk-weighting of assets in correctly measuring bank risk appears evident: the emerging negative relationship of RWA with beta confirms this bias, previously revealed by other European studies.

Obviously, we cannot generalize the explanatory model of fundamental beta tested here to different categories of banks. It is an industry-specific model, as international literature of the field suggests. Beta determinants (as well as their impacts), in fact, vary with varying bank dominant business. The sample considered here includes only commercial banks. Therefore, for different categories of banks, specific models should be tested. The model has the advantage of identifying the key-drivers of European bank systematic risk and measuring entity and sign of their impacts on beta. It could be concretely utilized to obtain an unbiased measure of true beta, in order to more accurately estimate the cost of capital of banks, or to measure betas of not listed banks (for which historical betas are not available, but economic and financial fundamentals do). However, for this practical use, the model should be verified in periods different from the estimation period. In addition, we should be aware that in more practical uses (for example, in estimating the exchange ratio in M&As among banks), a precise estimate of cost of capital is not required, but rather a relative comparison scale of betas and related costs of capital for the different banks involved in the deal.

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Notes

Note 1. Recent studies show how worst practices in estimating beta for M&As among banks (Venanzi, 2016) are widespread in Italy.

Note 2. If a large bank, with a complex structure, is experiencing severe distress conditions, its consolidation process increases the probability that liquidation/restructuring results to be more difficult or implemented more untidily. Since this kind of financial intermediaries implies that their problems could generate large and widespread risks, the concentration process can therefore involve an increase of probability that the distress conditions produce negative implications for the overall system.

Note 3. The log transformation was used because its distribution more nearly conforms to the properties of symmetry and normality.

Note 4. ECB official data (ECB, 2018), on the contrary, show that in the supervised 110 banks, the average NPL ratio decreases with increasing size (in the first quarter 2018, from 12.45% in banks with assets less than 30 billion euros to 4.08% in banks with assets larger than 330 billion and to 3.35% in global systemically important banks). These data are, however, biased by country effect, as ECB recognizes (that is the country mix in each size class differs). In addition, it is an average, weighted to the size (i.e. it is not necessarily representative of the banks in each size class, if banks are very different in size). In my study (Venanzi, 2017) on a sample of about 450 Italian commercial banks (using single balance sheet), a statistically significant relationship between size and NPL ratio does not emerge, but smaller banks are more frequent in more virtuous clusters for credit quality.

Note 5. ECB studies (ECB 2019) highlight a positive linkage between leverage and size.

Note 6. For example, the following SIC codes: 6211 (*Security Brokers, Dealers, and Flotation Companies*) for 33 banks, 6282 (*Investment Advice*) for 30 banks, 6311 (*Life Insurance*) for 20 banks, etc.

Note 7. We want to estimate a model which can explain both longitudinal and cross-sectional variability of beta.

Note 8. See Valipour and Vahed (2017) for a detailed literature review on this topic.