Systematic risk of European 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-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, we empirically estimate the fundamental betas of a sample of more than 100 European commercial banks in 2006-2015 period. 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 rules, does not correctly catch the bank risks, since it influences negatively their beta.
This evidence weakens the dominant belief 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

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: understanding which are the determinants of bank risk is crucial in order to better address country economic and financial policies as well as decision making of industry operators. 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 the bank 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 for estimating the cost of capital in M&As or asset management operations[1].

The international literature on bank risk is very wide-ranging. The various strands connect the total risk of bank (mainly, credit risk and bankruptcy risk) to different categories of determinants, among which bank characteristics, regulation policies, industry competition, deposit guarantee framework, etc.

This study, however, assumes a different perspective, partial and focused on a particular measure of a bank's systematic risk. In fact, the object is to empirically estimate a model that explains the beta of the European commercial bank stocks by means of a set of economic and financial fundamentals, provided by their financial statements. Therefore, we want to explain the systematic risk (neither specific risk nor total one) of banks and specifically, a measure of this risk, that is beta. By utilising 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 the fundamental beta, previously formulated for non-financial firms by the pioneering study of Beaver-Kettler-Scholes (1970), which seems to be very meaningful for financial companies for the following reasons:

- Capital Asset Pricing Model (hereinafter CAPM) is a pricing model that well functions in explaining the returns of bank stocks (Damodaran, 2009);
- the bank stock market (bank stocks are often leading in stock exchanges) is highly influenced by rumours and speculative behaviour which might distort the observed market prices, and therefore estimated historical betas; in addition, expectations about regulation and supervisory policies are further factors of return volatility;
- 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 returns (in excess of the risk-free rate) 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-De Jonghe-Vennet, 2007; Haq-Heaney, 2012), that appear more limited than those regarding U.S. banks (Leung-Taylor-Evans, 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 favour of both M&As among banks and a shift of the bank's business towards investment activities, that are riskier, to the disadvantage of traditional lending activity to the real economy, with obvious implications on moral hazard behaviour from bankers for the well-known "*too big to fail*"[2].

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

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

[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.

2. The theoretical and empirical framework

2.1. Measuring the systematic risk: the beta

Given the portfolio diversification theory, the relevant risk (that is the risk that needs 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, as follows:

$$(R_i - R_f) = \alpha_i + \beta_i * (R_{mkt} - R_f) + \varepsilon_i$$

$$\beta_i^{mkt} = \frac{cov_{i,mkt}}{\sigma_{mkt}^2} = \frac{\sigma_i * \sigma_{mkt} * corr_{i,mkt}}{\sigma_{mkt}^2} = \frac{\sigma_i * corr_{i,mkt}}{\sigma_{mkt}}$$

Market portfolio beta is obviously equal to 1 and therefore, if a stock has beta larger than 1, it means that its returns vary more proportionally than market portfolio returns (*aggressive stock*), and, if not, the stock is less sensitive to systematic risk (*defensive stock*).
There are many criticisms about beta:

- *ex post* using of past returns implies (rather questionably) that the realised returns were consistent with the future expectations that investors had before the returns took place;
- return frequency adopted in the regression can distort beta estimation. In practice, monthly returns are used, in a 5-year period (60 monthly returns in total). Daily returns would increase the observation number and therefore shorten the time span of the estimation (limiting the *bias* of not respecting the *coeteris paribus* assumption), but they could under-evaluate beta of less liquid stocks as well as over-evaluate the more liquid ones, that are often target of speculative behaviours;
- the choice of an appropriate *proxy* of market portfolio is a critical aspect, since, according with Roll (1977), the tests of the CAPM (Black-Jensen-Scholes, 1972; Fama-MacBeth, 1973; Fama-French, 1992) must be interpreted with great caution. In fact, they merely imply that the market index that was selected was ex post efficient, but they do not prove that the true market portfolio is ex post efficient, but unfortunately, because the market portfolio contains all assets, marketable and nonmarketable, it is impossible to observe;
- betas change over time as far as firms change (Damodaran, 1999): *i)* firms divest current businesses and invest in new businesses or acquire new firms. This process changes their business mix and therefore their beta; *ii)* they change their financial leverage, increasing or decreasing debt. In addition, decisions like paying dividends or buying-back shares change the financial leverage; analogously, variations in market value of equity or debt can cause relevant changes in financial leverage, also in short time; *iii)* more generally, firms tend to grow over time and in the same time their operating cost structures change, causing the change of their betas;
- multi-factor models (Fama-French, 1992 e 1993) undermined the CAPM/beta validity, showing that there are systematic risk components other than beta, in particular the *size-effect* (small firms have higher betas but also, coeteris paribus, stock returns higher than returns requested by CAPM) and the *book-to-market-value* premium (high book-to-market-value firms are considered riskier because with low growth perspectives, less profitable and low dividend paying): therefore, two more factors of systematic risk.

2.2. The fundamental beta

Many studies (Beaver-Kettler-Scholes, 1970; Bildersee, 1975; Eskew, 1979; Jarvela-Kozyra-Potter, 2009) affirm that corporate financial statements contain data and information that can be used for measuring risk. The question is: are 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 utilise 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 Beaver-Kettler-Scholes (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 accruals able to explain systematic risk by analysing correlations among betas and accounting fundamentals (correlations were also conducted at the portfolio level, since the portfolio, rather than the individual security, is the relevant decision-prediction entity for investors).
Finally, BKS utilised 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:

$$\beta_H = \beta_T + \omega$$

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):

$$\beta_T = \varphi_0 + \varphi_1 * z_1 + \dots + \varphi_n * z_n$$

where z_i are the accounting fundamentals and φ_i are the sensitivities of the true beta 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:

$$\beta_H = c_0 + c_1 * z_1 + \dots + c_n * z_n + \omega$$

The error term ω reflects error in β_H .
Therefore, removing the error (ω) from β_H we obtain the estimate of true beta, that is the fundamental beta (β_F).

$$\beta_F = \beta_H - \omega$$

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 analysed. The following relationship between the *true betas* of the two sub-periods is assumed:

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

Beta is assumed to be stable along the period: this hypothesis is confirmed by analysing the correlation between historical betas in the two sub-periods considered, at portfolio level.
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 order to form the portfolios,

the securities were ranked according both to the magnitude of historical beta and instrumental beta. In all cases, the fundamental beta has a better 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-Taylor-Walter (2013) show that the accrual variability 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. The final result is that the effect of the discretionary component on future stock return volatility is substantially lower and economically insignificant; therefore, fluctuations of stock returns mainly reflect a firm's fundamental uncertainty rather than managerial manipulation.

2.3. 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 payout** (BKS, 1970; Eskew, 1979; Jarvela-Kozyra-Potter, 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 payout ratios are riskier. The belief can be rationalized by the signalling 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-Gupta-Nanisetty, 1998), firms follow a policy of dividend stabilization (i.e., firms are reluctant to cut back, once a dividend level has been established), and the payout 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 payout: firms with lower payout ratios, ceteris paribus, will have higher growth rates. Yet it was argued above that low payout implies greater riskiness. If so, then growth rate would be positively associated with risk;
- **leverage**: as debt is introduced, the earnings stream of the common stockholders becomes more volatile (Modigliani-Miller, 1958). According to the second proposition of Modigliani & Miller theory, the levered cost of capital of a firm increases as far as the market value of debt divided market equity increases

  $$r_e = r_u + \frac{D}{E} * (r_u - r_d)$$

  where:
  $r_e = levered\ cost\ of\ capital; r_u = unlevered\ costo\ of\ capital\ ; r_d = cost\ of\ debt.$

  According with CAPM, the relationship between returns lead to the corresponding relation between betas:

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

- **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 (the log transformation was used because its distribution more nearly conforms to the properties of symmetry and normality): 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-Kim, 1998; Titman-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 and better diversification opportunities. In addition, larger firms can realize scale economies and therefore reduce the incidence of direct bankruptcy costs on company value (Ang-Chua-McConnell, 1982; Warner, 1977). Finally, Fama-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-Kozyra-Potter, 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

$$\beta_{accounting} = \frac{cov(\frac{E_t}{P_{t-1}}, M_t)}{var(M_t)}$$

where $M_t = (\sum_{i=1}^{N} E_{it}/P_{it-1})/N$. It is positive the expected link, 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-Kozyra-Potter (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 payout* does not explain beta for larger companies. This evidence can be explained by the fact that the larger companies, although financially strong and able to pay dividends, can adopt discretionary dividend policies and investors did not evaluate a lower payout negatively (i.e. as insufficient cash flows generated), but as a strategy based on other reasons; on the contrary, for small firms, a low payout is interpreted as a symptom of larger risk, because they are considered more financially vulnerable. In addition, earnings volatility has a very weak impact on beta, although statically significant. The authors explain this evidence through the speculative bubbles that distort E/P ratios in the last years.

2.4. The drivers of bank beta

Many recent studies focus on identifying drivers of bank systematic risk. We will analyse 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 regulatory constrained. Baele-De Jonghe-Vander Vennet (2007) discuss costs and benefits of diversification in term of profitability and risk.
First, the formation of financial conglomerates would be beneficial if there are positive cost and/or revenue effects from combining various financial services activities. Consolidated revenues would be improved if the income-generating capacity of the combined institutions is enhanced. Similarly, the operating costs of financial conglomerates would be lower relative to specialized banks if integration leads to operational synergies, e.g. through economies of scope. The sharing of inputs such as labour, technology and information across multiple outputs constitutes the major source of such potential cost savings. Second, 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 valuations. Third, 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 dimension, standard portfolio theory predicts that the combined cash flows from non-correlated revenue sources should be more stable than the constituent parts. Securities and insurance activities have the potential to decrease conglomerate risk, but the effect largely depends on the type of diversifying activities that bank holding companies undertake. However, we know that diversification can simply pursue 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. Managers may pursue diversification to enhance their ability to extract private benefits, even when diversification would lower the market value. The question is whether or not internal mechanisms can be designed to align interests or whether external discipline can alleviate some of the agency problems. In addition, on the costs side, 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, empirically many studies (Stiroh – Rumble, 2006; Stiroh, 2004 and 2006; DeYoung – Roland, 2001; Baele – De Jonghe – Vander Vennet, 2007; Demirguc-Kunt – Huizinga, 2010) show a significant positive link between non-interest income (non-interest income captures all income streams that functionally diversified banks generate by providing a broad array of financial services) and the 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. The above empirical findings show that more diversified banks have a higher exposure to changes in market sentiment (e.g. because of their reliance on investment banking) 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 result 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 less groups of firms to which they can lend, they can pursue a better monitoring of their borrowers)[3].

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 behaviour), 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

[3] 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 billions of euros to 4,08% in banks with assets larger than 330 billions 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.

risk and size. Their study, conducted on a sample of 117 European commercial banks (from 15 European countries) in the 1996-2010 period, highlights that size significantly increases systematic and total risk, while decreases the idiosyncratic one. These results are substantially confirmed in Baele-De Jonghe-Vennet (2007) study, regarding European banks too.

As far as studies on U.S. banks are concerned (Stiroh, 2006 e Leung-Taylor-Evans, 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 reduces as their equity stake decreases. Moreover, bank capital regulation suggest 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. That is, for low levels of capital, as a bank's capital increases, it takes on less risk, reflecting the disciplinary effect of bank capital, but as capital continues to rise, banks eventually reach a point where further increases in bank capital result in increasing risk. The authors argue that this 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 state insurance on deposits (moral hazard problem). Their empirical results support the nonlinear linkage of CET1 with beta. In Leung-Taylor-Evans (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. It has proven difficult for investors and regulators to identify the actual level of risk. The off-balance sheet activities of most concern here are the contingent liabilities of the banks where the bank must honour guarantees when required. The theoretical literature assumes that they increase bank risk and empirical findings prove this impact;
3. **dividend payout,** whose impact on beta is assumed negative, as in non-financial firms (see§ 2.3);
4. **incidence of non-performing loans:** Leung-Taylor-Evans (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-De Jonghe-Vennet, 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. Tested hypotheses

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 behaviour favours moral hazard attitude: large banks become “too big to fail” and this could increase the incentive for large banks to undertake riskier non-interest generating activities. Moreover banks, becoming 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 payout

According with the signalling theory (Lintner, 1956; Fama-Babiak, 1968; Bharati-Gupta-Nanisetty, 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, payout ratio can be viewed as a surrogate for management's perception of the uncertainty associated with the firm's earnings: higher payout 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 the 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 penalise 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 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 findings from Mediobanca-Ricerche & Studi annual report on international banks (Mediobanca-R&S, 2014; Barbaresco, 2015): counter-intuitive positive linkage of RWA/total assets ratio 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 penalise 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 utilised 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-Haselmann-Vig, 2016; Cannata-Casellina-Guidi, 2012).

H5. Capital adequacy lessens systematic risk

According with Haq-Heaney (2012), a higher Tier1 (the main components of equity capital) functions as a capital buffer for absorbing potential future losses and reducing distress costs (through less debt). In addition, higher net worth means less agency costs.

Differently from previous studies, here we don’t measure capital adequacy using CET1. Firstly, since CET1 is highly correlated with RWA (Pearson coefficient is -38%); secondly, because the assumed distortion in calculating RWA (see above) could also bias CET1 (so explaining why this indicator was not able to distinguish between virtuous and bankrupt banks, in recent crisis).

Here we will use TEXAS ratio (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, loans are the most part of assets, credit risk is the main component of total risk and therefore capital adequacy might be better measured by how equity capital faces up to *shortfalls* deriving by NPL write-down. In addition, among the determinants of beta (see hypothesis 9 below) leverage is included (since it is calculated using Tier1, it can make up for the lack of CET1).
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-De Jonghe-Vennet (2007), better performing banks in terms of superior technology and more skilled management (Baselga-Pascual et al., 2015) will be perceived less risky by market, but no impact is expected on systematic risk (otherwise inefficiency increases a bank's 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 market. We assume the intangibles are opaque because their value written in 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), not considered by the Basel II framework since considered rough, showed to be more effective than more common indicators (for example in comparison with CET1) in forecasting bank distress in recent crisis (BCBS, 2014). In fact, Basel III re-introduces it among indicators to be controlled.
However, bank leverage has a different 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) e Leung-Taylor-Evans (2015).
Moreover, leverage might affect idiosyncratic risk more than systematic one: if a bank monitors total risk, the leverage impact on systematic risk could be negative, since higher systematic risk can induce strategies that don't enhance leverage. In addition, if leverage affects returns, its impact on beta might be distorted by 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) [4].

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 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 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).
However, the sample homogeneity in terms of dominant business does not exclude other business lines in bank activity [5].

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[4] ECB studies/statistics (ECB, 2019) highlight a positive linkage between leverage and size.

[5] 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.

Further detail on the sample is provided in Tables 1, 2 and 3.

The sample is very variegated in terms of size, as dispersion coefficients show (see Table 2). On average, assets amount to 263 billions of euros, and the half of sample has assets lower than 23,5 billions. Even though sample includes only listed banks, there is not lack of smaller ones: the 5% of distribution has assets less than 2 billions and employees less than 62.

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**

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.

Table 2 – Sample by size

	Total assets (billions of euros)	*Number of employees*
mean	263.5	17,999
median	23.5	1,838
5° percentile	2.0	62
95° 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
5° percentile (%)	37.9	23.2
95° percentile (%)	90.8	80.6
coefficient of variation	0.23	0.34
interquartile range/median	0.28	0.52

3.3. Variables, tested model and statistical methodology

Datastream beta is yearly calculated, 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 listing country stock market) (if multi-listed stocks, the first listing market is considered).
Table 4 shows the determinants of beta, highlighting the related methods of calculation.
In addition to variables 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 asstes are higher than 50 billion euros) and *dummy's* (equal to 1 when assets do not overcome 50 billions). This *dummy* should distinguish banks that utilise internal ratings from banks that adopt standard ratings. This is a *proxy*, that is based on size for distinguishing 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. Behn-Haselmann-Vig (2016) show that the *probability of default* (PD) of banks utilizing IRB system are lower than those utilizing standard system. Recently, also the Basel Committee highlighted the pitfalls of IRB system, introducing in the regulatory framework appropriate correction mechanisms;
- between PAYOUT and TEXAS ratio, on the one hand, and dummy_CRISIS, on the other, to verify if the impacts have differed during the years of the recent financial crisis (2008-2010). For example, we can assume that, according with signalling 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 (probably better than fixed effect) and country economic scenario (in terms of cycle and inflation).

The tested model is the following:

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

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[6] (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).

Table 4 – Determinants of beta

determinants	*symbol*	*calculation*
size	SIZE	ln (total assets)
diversification	DIV	noninterest revenues/total revenues
dividend payout	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

[6] We want to estimate a model which can explain both longitudinal and cross-sectional variability of beta.

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
dummies country	DCOUNTRY_Austria…..DCOUNTRY_UK	=1 if belonging to country

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.

Table 5 – Descriptive statistics of beta

mean	0.77
median	0.68
5° percentile	0.04
95° percentile	1.89
coefficient of variation	0.80
interquartile range/median	1.38

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 of 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	

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 incidences: correlation signs that 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 payout 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 descriptive statistics of the determinants of beta, since data of some years are not available and, therefore, sample mix is not homogeneous over the years.

From Table 7 we can see that, on average, noninterest revenues are about a quarter of total; omitting distribution tales, we have a range of variation from 8% to 57%, that confirms the differences among the banks in the sample, in terms of relevance of investment assets, besides the dominant traditional business of credit intermediation.

Payout is on average equal to 30%, the incidence on income of operational costs is 78%, derivatives are only 2% of assets, but in UK and German banks they reach average values four times greater and in South European countries (i.e. Italy, Greece, Portugal and Spain) assume lower values.

As far as RWA intensity is concerned, sample average is equal to 57%, with higher values in South European countries. Median value of leverage is about 8, which means a Tier1 equal to 12,5% of total assets.

Finally, TEXAS ratio has an average value of 60% (but the median value is half of mean); the indicator is higher than 100% (that means a *shortfall* of equity capital in case of write-off of the NPLs) in Greece, Ireland and Italy (for brevity, descriptive statistics per country are omitted).

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 payout, on the contrary, decreases beta (according to hypothesis 3), signalling to the market about expected earnings; 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 proxy used is weak, since *intangibles* are too generical and non-analytical category, since they can include many different components (data on detail are not available).

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						

In contrast to 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 from 1 to 4, but the sign is opposite to what is expected: we can explain this evidence highlighting that leverage affects bank 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 of opposite sign (and reverse causal link). In addition, as 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) how the impact of leverage on systematic risk is likely to be absorbed by the country effect: in fact, when country *dummies* are introduced, leverage coefficient 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 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 not-significant coefficients are obtained: see, for example, Haq-Heaney (2012) e Leung-Taylor-Evans (2015).

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

The variable *GDP_index,* in regressions where it is statistically significant (where country fixed effects are omitted) negatively affects bank beta: in growing economies, market risk is lower (as previous empirical findings confirm). 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 variable 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 respective country dummy.

The apparently weak relevance of country's 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 have to consider the following issues: *a)* the sample countries are all members of the EU (all 28 member states), with the exception of Swiss banks. Therefore, if we consider the global nature of financial systems, these countries are relatively homogeneous from the perspective of beta; *b)* betas in Datastream are calculated through the well-known time-series regressions between 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, that is the stock return sensibility to market index of country whom banks belongs to: therefore, it could be theoretically neutral with respect to geographical differences among sample observations. We mean that the country economic and financial characteristics do affect returns and volatility of bank stocks, as well as 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; *c)* if we analyse the residual errors of model 5 (the most complete one), we do not observe higher errors in some countries in comparison to others, in particular not for Switzerland or the United Kingdom, which are countries that are potentially less homogeneous with respect to other sample countries.

The most complete model (model 5) shows a very good explanatory power: it explains more than two thirds of beta variance (both longitudinal and cross-sectional).

This study presents some limits, discussed as follows.
Firstly, the presence of missing values: from an original sample of 149 banks, we arrived at 112 banks, since some determinants (in particular incidence of derivatives and TEXAS ratio) were not available for some banks (however, we always had a minimum of 5 year observations per bank).
Secondly, proxies of some determinants could be measured more accurately, for example asset opacity: off-balance sheet items (according to some empirical studies) might improve the measurement of impact of this determinant on beta.
Thirdly, other explanatory variables of beta could be included among regressors. However, this inclusion could be problematic, since there is collinearity among economic and financial fundamentals of banks. A factor analysis can resolve this problem, by expressing determinants as latent factors, that are linear combinations of observable elementary variables (in this way it is possible to divide the multiple impact of some proxies among different determinants). However, this step can complicate the practical uses of fundamental beta.

3.4.3. Preliminary conclusions

From the empirical test on a sample of more than 100 European commercial banks in 2006-2015 decade, size and diversification of assets (which increases with increasing size) result to increase bank systematic risk. This empirical evidence should suggest that regulators (both European and national) correct their current orientation in favour of mergers and acquisitions among banks as a panacea for all the evils of the banking system, affirming that concentration increases system stability (Venanzi, 2018).

As shown by many studies, increasing size incentivizes moral hazard behaviour of bank managers, related to the *too big to fail* effect and creates a lot of interdependence among larger and complex financial institutions. Managers are encouraged to undertake riskier activities (that could generate much profits), relying on government protection.

Larger size, in addition, generates the following consequences: *i)* makes bank activities more complex and therefore more difficult to assess and monitor risk exposition, from both managers/internal controllers and 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).

Larger size generally causes a business mix more oriented to activities that are different from traditional credit intermediation (trading, for example), increasing riskier non-interest revenues; the results obtained from this study indicate 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 more 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.

Moreover, this orientation to the consolidation among banks happens in the current context, characterized by a high concentration degree of European and global banking system, paradoxically improved by the recent crisis and consequent public bailouts (6 mega-mergers after 2007 in USA and 4 in Europe). The current landscape of bank institutions appears very scary for gigantism (Mediobanca-R&S, 2014). The main 33 European banks had net assets (excluding derivatives) double than European GDP, on average, in 2004-2013 decade (assets of the main 13 USA banks were equal to 60% of GDP). In Switzerland and Netherlands, the first banks in 2013 has assets about three times GDP, in France, Spain and United Kingdom from two to one and half, in Italy equal to GDP, in Germany 80% [7]. If we compare the average assets of European banks to those of European non-financial multinationals, the ratio is of 11,4 to 1 (Venanzi, 2018).

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

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[7] Comparing bank net assets to GDP is not correct, since they are not homogeneous figures (fund the former, flow the latter) ; however, it can be a sign (although rough) of the big size reached by financial intermediaries.

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