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Assessing the relevance of the Basel III ratios

An empirical study using an option pricing default prediction model

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In the aftermath of the recent financial crisis, several shortcomings in the regulations of banks were revealed. As a response the Basel Committee on Banking Supervision presented a new standard, Basel III, with the aim of preventing future bank defaults. This study evaluates the relevance of four Basel III capital and liquidity ratios for reducing the probability of bank default. The investigated ratios are the tier 1 capital ratio, the leverage ratio, the liquidity coverage ratio and the net stable funding ratio. The empirical study includes 145 European and US banks over the time period 2006 to 2015. We model equity as a down-and-out call option on the bank's assets and obtain an annual default risk measure that considers default risk over time, dividend and coupon payments, as well as incorporates expected asset returns, as opposed to the risk-free rate. We then examine the association between the four Basel III ratios and the probability of default. Similar to previous research we are not able to find support for higher levels of the Basel ratios being associated with lower probabilities of default, which suggests that the Basel III capital and liquidity ratios might not be relevant for reducing default risk.

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1. Introduction

In the aftermath of the financial crisis of 2008, several shortcomings in the regulations of banks were revealed. Numerous banks worldwide were found to have excessive leverage, inadequate and low-quality capital, as well as insufficient liquidity to cover for short-term losses. In total, 414 US banks filed for bankruptcy during the years 2008 to 2011 (Federal Deposit Insurance Corporation, 2016). The number of European bank failures was much lower, however, European governments financially supported their banks with EUR 1,615.9 billion, corresponding to 12.8% of EU GDP (European Commission, 2012). Even banks that had previously presented high capital ratios (e.g. Royal Bank of Scotland, Lloyds Banking Group and UBS), relied on their governments for financial aid. Following the financial crisis, the Basel Committee on Banking Supervision (BCBS) acknowledged the need for new regulations, and in December 2010, Basel III was presented, with the aim of strengthening the banking system and limiting the risk of future bank defaults. Central in the framework are four ratios that will be used as means to ensure the quality and level of bank capital and liquidity; the tier 1 capital ratio, the leverage ratio (in this study renamed the Basel equity ratio since the ratio in fact measures equity), the liquidity coverage ratio and the net stable funding ratio (BCBS, 2011a). Due to the strong focus on these four measures, researchers have started to investigate the Basel ratios' usefulness in actually preventing bank failures. Particularly the tier 1 capital ratio has been criticized as it allows banks to use internal methods in the calculation of the ratio. Blundell-Wignall and Roulet (2012), Milne (2014) and Flannery and Giacomini (2015) all investigate the tier 1 capital ratio, but find no support for it to be a useful tool for predicting bank failures. Hong, Huang and Wu (2014) make an attempt to calculate the liquidity coverage ratio and the net stable funding ratio, but only find limited support for the ratios having any effect on default risk. Hartlage (2012) even argue that the liquidity coverage ratio works to undermine the financial system.

As starting point for this paper, we use the study by Blundell-Wignall and Roulet (2012), which in a relatively simple and clever way questions the relevance of the tier 1 capital ratio. The authors use a market-based method developed by Merton (1974) to model the default risk measure distance-to-default for a large sample of banks to perform a regression analysis with the distance-to-default as the dependent variable and the tier 1 capital ratio as one of the independent variables. No support is found for the tier 1 capital ratio as a predictor of default risk. Given the amount of regulatory focus on the tier 1 capital ratio, it is important to investigate the measure further to understand whether regulators and policymakers focus on relevant measures. Essential for this sort of analysis is to assess the Basel ratios in relation to a default risk measure that accurately reflects reality. We identify four adjustments that can be made to the distance-to-default measure in order to arrive at such a measure. The first adjustment is to consider that default can occur over time and not only at a specific point in time. Secondly, the distance-to-default measure is based on estimated market values of assets and should therefore consider cash outflows affecting the value of the firm's assets, such as dividend payouts and coupon payments. Thirdly, real world probabilities are more accurate than risk-neutral ones and the calculation of the default risk measure should therefore incorporate the expected asset returns instead of the risk-free rate. Fourthly, we consider it necessary to transform the distance-to-default measure into an actual probability measure as we find probabilities more intuitive to analyze than the distance-to-defaults.

Following the above reasoning, this study uses a barrier option model, more specifically a down-and-out call option (DOC) model, to estimate the probability of default for 145 European and US banks over the years 2006 to 2015. The obtained measure of default risk considers the four aspects ignored by Blundell-Wignall and Roulet (2012). Thereafter, we perform a regression analysis to examine the association between bank default probabilities and the Basel ratios. In contrast to Blundell-Wignall and Roulet we extend the analysis to not only include the tier 1 capital ratio, but also the Basel equity ratio, the liquidity coverage ratio and the net stable funding ratio. Building on the purpose of the Basel ratios, i.e. to prevent bank failures, we hypothesize all four ratios to have a negative impact on the probability of default, meaning that higher capital and liquidity ratios should decrease the default risk. We further hypothesize that the Basel equity ratio should have a more significant negative impact on the probability of default than the tier 1 capital ratio.

Similar to previous research (e.g. Blundell-Wignall and Roulet, 2012; Hartlage, 2012; Milne, 2014; Flannery et al. 2015) we find no supporting evidence for the Basel ratios having negative associations with the probability of default, which suggests that the Basel III ratios might not be relevant for decreasing the probability of default. However, we find a significant association between the regular equity ratio and the probability of default, which seems contradictory as no association is found for the Basel equity ratio, which is rather similar to the regular equity ratio. A possible explanation for this result is found in the numerators of the two measures, namely the tier 1 capital and the book value of equity.

The thesis proceeds as follows; *Section 2* is devoted to previous literature where we give a background on the focus of the Basel Accords and present previous research on the Basel ratios, as well as default prediction models. In *Section* 3 we discuss the focus of this study in relation to previous research, and consequently state our hypotheses. *Section 4* presents information on the data sample, while in *Section 5* we describe the method used in this study. In *Section 6* we present our results, and finally, we summarize our main findings and conclusions as well as suggestions for future research in *Section 7* and *8*.

2. Background and previous research

Since this paper aims to investigate the usefulness of the Basel capital and liquidity ratios in preventing bank failures, the following section provides a brief history on the Basel Accords, with a primary focus on the development of these ratios. Subsequently, we present previous research focusing on the relations between the Basel ratios and the probability of default. Thereafter, previous literature on default prediction is explored. We present the two main streams of research, as well as studies that have compared the relative effectiveness of those streams. Finally, we present a more detailed overview of option pricing models for default prediction.

2.1 Background on the Basel Committee and the Basel Accords

In the early 1970s, numerous banks worldwide suffered large foreign currency losses, which resulted in subsequent disruptions in the international banking markets. In response to these disruptions, the Basel Committee on Banking Supervision (BCBS) was founded in 1974 by the central bank governors of the G10 countries[1]. The committee is still active today and its purpose is to enhance financial stability through strengthening of regulations, supervision and practices of banks globally. BCBS formulates minimum standards and guidelines that have no legal power. Instead, it is the responsibility of the national authorities of the committee member states to implement the standards, which results in differences between implementations of the framework in the 28 member jurisdictions (BCBS, 2015).

[1] G10 is made up by 11 countries; Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States.

The first Basel Accord, Basel I, was released to banks in 1988 with capital adequacy, i.e. the level of capital a bank has to hold in relation to its assets, as the primary focus. Both guidelines on the measurement of capital adequacy as well as minimum standards were introduced in the framework. The key element of capital was emphasized as being a bank's core capital, commonly referred to as the tier 1 capital, consisting of paid up share capital/common stock and disclosed reserves (e.g. retained earnings). As explained by BCBS, differences between national fiscal systems may affect the comparability of banks' capital positions, but the core capital is still "*the only element common to all countries' banking systems; it is wholly visible in the published accounts and is the basis on which most market judgements of capital adequacy are made; and it has a crucial bearing on profit margins and a bank's ability to compete*." (BCBS, 1988, pp. 2-3). For the purpose of capital adequacy assessment, BCBS decided risk-weighted assets (RWA) to be the primary measure to which the tier 1 capital would be compared to. Total RWA is calculated by multiplying the value of different asset categories (both on and off-balance sheet exposures) with different risk-weights[2] (BCBS, 1988). By comparing the tier 1 capital of a bank with the RWA, the tier 1 capital ratio is obtained:

$$Tier\ 1\ capital\ ratio\ = \frac{tier\ 1\ capital}{risk-weighted\ assets} \tag{1}$$

Notably, the definition of tier 1 capital has developed slightly over the years, more specifically, the criteria for which securities can qualify as tier 1 capital has changed.

The importance of the Basel I capital requirements was not only recognized by the BCBS member countries, but also by non-members, and the framework was consequently introduced to essentially all countries with internationally active banks (BCBS, 2015). During the years after the introduction of Basel I, several amendments were made to the standard and in 2004 Basel II was published, extending the scope of the Basel Accords through the introduction of three pillars, namely:

1. Minimum capital requirements, which sought to develop and expand the standardized rules set out in the 1988 Accord
2. Supervisory review of an institution's capital adequacy and internal assessment process
3. Effective use of disclosure as a lever to strengthen market discipline and encourage sound banking practices (BCBS, 2006).

[2] In Basel I from 1988, five risk-weights were allowed; 0, 10, 20, 50 and 100%.

In addition to these three pillars, Basel II put additional focus on the riskiness associated with the RWA. In contrast to the first Basel Accord, Basel II allowed for advanced approaches in the calculation of RWA as an alternative to the standardized approach applied by Basel I (BCBS, 2006). Using the advanced approaches meant developing internal models for valuing the RWA. As discussed by BCBS, the assumptions made by banks in these internal models affect the generated capital requirement for the bank and large differences can therefore be found between banks (BCBS, 2011b). In the US, only large[3] internationally active banks had to adhere to the standard, while all other banks could choose between Basel I and Basel II. In Europe, the standard was applied to all banks, irrespective of international involvement, and to all investment firms (Dierick, Pires, Scheicher and Gereon Spitzer, 2005).

After the financial turmoil starting in 2008 it became evident that banks worldwide had entered the financial crisis with excess leverage, poor quality of capital and inadequate liquidity buffers. Banks were also found to have poor risk management and inappropriate incentive structures, demonstrated by the mispricing of both credit and liquidity risk (BCBS, 2015). In order to respond to the weaknesses in the regulation, Basel II was further developed into a third Basel Accord, presented in December 2010. The purpose of the third Accord was to improve the banking sector's ability to absorb shocks arising from financial and economic stress.

Basel III places further emphasis on capital adequacy, both related to the minimum level of capital and the quality of the capital. The definition of the tier 1 capital was updated in this new standard and is more restrictive regarding the inclusion of hybrid capital. In addition, amendments to the two allowed approaches for calculation of RWA were also made, making the standardized approaches more risk-sensitive and the new advanced approaches more complex than the ones in Basel II (BCBS, 2011a). Moreover, Basel III introduces a number of new elements, such as the Basel equity ratio and two liquidity requirements in form of the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The Basel equity ratio is defined as tier 1 capital divided by total assets (including both on and off-balance sheet exposures). Similar to the tier 1 capital ratio the aim of the Basel equity ratio is to secure that banks have sufficient capital levels to absorb potential losses. Contrary to the tier 1 capital ratio, the Basel equity ratio is not affected by risk-weights. The LCR is a minimum liquidity ratio, requiring banks to have enough high-quality liquid assets to survive a 30-day period of stress.

[3] Large banks are defined as banks with consolidated assets over USD 250 billion and foreign exposure of at least USD 10 billion.

Lastly, the NSFR is defined as available amount of stable funding divided by required amount of stable funding, i.e. sources of funding divided by uses of funding (BCBS, 2011a). The assets and liabilities are assigned different weights when calculating the measure. Long-term interest-bearing debt and equity are considered to be sources of funding, while loans to consumers and companies are considered to be uses of funding (BCBS, 2014). To summarize the three ratios are defined as follows:

$$Leverage\ ratio = \frac{tier\ 1\ capital}{total\ assets\ including\ off-balance\ sheet\ exposures} \tag{2}$$

$$Liquidity\ coverage\ ratio = \frac{high\ quality\ liquid\ assets}{total\ net\ liquidity\ outflows\ over\ the\ next\ 30\ days^{4}} \tag{3}$$

$$Net\ stable\ funding\ ratio = \frac{long-term\ interest-bearing\ debt\ and\ equity}{loans\ to\ consumers\ and\ companies} \tag{4}$$

The third Basel Accord is gradually being implemented between 2013 and 2019. In January 2015, the updated tier 1 capital ratio, the Basel equity ratio and LCR had started to be implemented, with a scheduled increase in the levels of the minimum requirements during the implementation period. With regard to the NSFR, the minimum requirements will be introduced at the end of the implementation period, in 2018 (BCBS, 2011a). Finally, in contrast to Basel II, the US implementation of the Basel III also applies to financial services firms with more than USD 50 billion in consolidated assets, in addition to the internationally active banks (Federal Reserve System, 2012).

2.2 Recent empirics on bank defaults and the Basel ratios

Comparatively few studies focusing on the linkages between the Basel ratios and the probability of default have been published. However, the recent financial crisis and the announcement of the third Basel Accord in 2010, have added traction to this area and in 2012, Blundell-Wignall and Roulet questioned the effectiveness of the tier 1 capital ratio as a regulatory tool. Using the option pricing model introduced by Merton (1974), Blundell-Wignall and Roulet calculate the distance-to-default (i.e. the number of standard deviations away from the default point) for an unbalanced panel of 94 European and US internationally active banks over the period 2004 to 2011. Thereafter a regression analysis is performed, investigating the association between the

[4] Under a significantly severe liquidity stress condition.

distance-to-default and the tier 1 capital ratio. The model controls for both macro and micro variables, namely market beta of each bank, house prices, relative size, derivatives gross market value of exposure, trading assets, wholesale funding and cross-border revenue. No support is found for the tier 1 capital ratio as a predictor of default risk. Additionally, the regression is also performed with an inversed equity ratio (dividing total assets with equity), replacing the tier 1 capital ratio in the regression. The result of this analysis shows that this simple ratio is a more powerful predictor of default risk. Furthermore, Blundell-Wignall and Roulet find strong support for house prices being associated with the distance-to-default. Consequently, the authors argue that the Basel framework is overly complex and puts too much emphasis on the risk-weighted tier 1 capital ratio.

Other studies have also analyzed bank default risk and included the tier 1 capital ratio in their studies. However, the main focus of these studies has not been to assess the relation between the ratio and default probability. Milne (2014) evaluates the predictive power of the Merton distance-to-default measure and calculates distance-to-default on a half-year basis between 2006 and 2011 for the 41 largest global banking institutions during that period. The distance-to-default is found to decrease the closer it gets to the end of 2008, representing an increase in the default risk. The predictive power of the distance-to-default is analyzed using a multivariate regression, where the percentage decrease in share price or a dummy variable of actual failure or survival is the dependent variable and the distance-to-default is one of the independent variables. The tier 1 capital ratio is included as a control variable but no support is found for it as a predictor of fall in share prices or actual failure. Furthermore, Flannery and Giacomini (2015) study a total of 38 European banks over the years 1997 to 2011. The main focus of the study is on how supervisors handled European banks during the financial crisis, and the authors show that early regulatory attention to decreases in bank equity value can substantially reduce government costs of dealing with bank losses. As part of the analysis, probabilities of default are calculated using Merton's (1974) framework and the associations of different determinants of the probability of default is assessed. In line with Blundell-Wignall and Roulet (2012) and Milne (2014), no support is found for the tier 1 capital ratio as a predictive tool for probability of default.

With regard to the two liquidity ratios of Basel III, Hong et al. (2014) are one of the first to attempt to calculate the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The study is based on a sample of 9,349 US commercial banks over the period 2001 to 2011. Main findings are that the LCR is found to be lower prior to 2007 and that banks increased their liquidity buffers after 2007. This is explained with the observation that banks for preventive purposes increase their liquidity buffers when anticipating financial distress. However, the LCR is not found to have any significant power for predicting bank failures. With regard to the NSFR, the ratio is found to be significantly negatively associated with the probability of default, but with limited impact. Furthermore, the authors find systemic liquidity risk to be a major contributor to bank failures in the years 2009 and 2010 and suggest that regulatory frameworks for liquidity risk should address both liquidity risk on the individual bank level and on the system level. Hong et al. also find large banks to have lower default risk and explain this with the too-big-to-fail problem, meaning that large banks tend to receive government support if the default risk becomes too large. Additionally, Hartlage (2012) studies the LCR and argues that the ratio works to undermine the stability of the financial system rather than reducing the systemic risk. A simple model of bank liquidity is used to demonstrate how certain strategies for complying with the LCR requirement may cause banks to increase borrowing to unsustainable levels.

2.3 Default prediction

From the focus of the Basel Accords it is apparent that prevention of future bank defaults is one of the main objectives. As shown, prior research has therefore studied the association between default risk and the regulatory tools provided by the Basel Accords. When performing this type of analysis, it is of importance to evaluate the Basel ratios in relation to an accurate default risk measure. In this section we therefore explore default prediction models that can be used to assess the relevance of the Basel ratios. We start by presenting the two main streams of default prediction models; the accounting-based and the market-based models, followed by a more detailed overview of the technical aspects of option pricing frameworks for default prediction.

2.3.1 Accounting vs. market-based approaches

The accounting-based models are characterized by their usage of financial statement information for predicting default. The studies commonly use single or multiple financial ratios, such as profitability, liquidity and solvency ratios, to create models that can discriminate between defaulting and non-defaulting firms. Beaver (1966, 1968) performs a univariate analysis of different financial ratios and sets the stage for models using other approaches, such as multivariate discriminant analysis (Altman, 1968), logistic regression analysis (Ohlson, 1980) and probit regression analysis (Skogsvik, 1988). Through these models, a score is calculated. Altman (1968), for example, develops a Z-score and classifies firms with Z-scores lower than a specific cut-off point as financially distressed. Ohlson (1980) develops an O-score and Skogsvik (1988) a V-score, and unlike the Z-score these two scores can be transposed into actual probabilities of default. The creation of accounting-based models requires actual defaults in the sample in order to identify characteristics that can discriminate between defaulted and non-defaulted firms and consequently, these techniques heavily depend on the definition of default. Altman (1968) defines default as a firm filing for bankruptcy petition under Chapter X of the National Bankruptcy Act and Skogsvik (1988) uses a broader definition that includes both firms filing for bankruptcy according to Swedish regulation, firms voluntarily shutting down and firms receiving government subsidies.

Contrary to the accounting-based models, the market-based models estimate default risk through an assessment of the firm's debt structure and the market value of the firm's assets. Most market-based models are based on option pricing theory that can be traced back to the seminal work of Merton (1974), who introduces a basic approach for the valuation of stocks and corporate bonds as derivatives on the firm's assets. The model builds on ideas that are implicit in the option pricing methodology of Black and Scholes (1973). Merton (1974) observes that the firm's equity can be viewed as a standard European call option on the value of the firm's assets. Equity holders have the residual claim on the firm's assets after all of the debt has been paid, i.e. limited liability in case of firm default. The payoffs to equity thereby reflect the payoffs to a call option. If the value of the firm's assets at time T, the maturity date of debt, is greater than the value of debt that the firm has to repay on that date, equity holders will exercise their option and repay the debtholders. In other words, the firm then continues to exist. However, if the value of assets at time T does not exceed the value of the debt, equity holders leave the option unexercised and the firm defaults. The probability of each possibility is reflected in the Black and Scholes (1973) model, and affects the value of the call option. Moreover, the Merton model uses estimates of unobservable market values of assets and asset return volatilities in the application of the model.

The Merton model is the foundation of many market-based default prediction models and an extension of the model has been commercially implemented by Moody's KMV, one of the largest providers of credit-risk measurement in the US. Together with the Merton model, the KMV methods are commonly used in empirical studies employing market-based methods (see Keenan and Sobehart, 1999; Sobehart, Keenan and Stein, 2000; Crosbie and Bohn, 2003 for some of the KMV methods).

Prior research has evaluated and compared the accounting-based and the market-based models' abilities to predict actual defaults. For example, Hillegeist, Keating, Cram and Lundstedt (2004) compare the results of the Merton model to the models of Altman (1968) and Ohlson (1980), and find the Merton model to outperform both Altman's Z-score and Ohlson's O-score. Gharghori, Chan and Faff (2006) assess the effectiveness of two different market-based prediction models and compare them to an accounting-based model similar to Altman's (1968) model. The market-based models are also in this case found to clearly outperform the accounting-based model. Both Hillegeist et al. (2004) and Gharghori et al. (2006) argue that accounting data reflects past performance and is therefore insufficient for predicting a firm's future state, and highlight that accounting data builds on several accounting principles such as the going-concern principle and the principle of conservatism, which affects the predictive power of the probability measure. Under the going-concern principle it is already assumed that the firm will continue to exist and under the principle of conservatism asset values are often understated, which in turn creates overstated leverage ratios that affect the accuracy of the estimated probability of default. Moreover, it is noteworthy that the accounting-based models are constructed using firms from the same industry (e.g. Altman and Skogsvik study solely manufacturing firms and Ohlson industrial firms), and as accounting ratios often vary between industries, models may not be directly applicable to other industries (Gharghori, Chan and Faff; 2006). On the other hand, also the market-based models have been criticized, e.g. for not accurately reflecting all of the information available in the financial statements (e.g. Sloan, 1996). Saunders and Allen (2002) point out that the Merton model builds on too many strict assumptions, such as the firm only having one type of debt. Furthermore, the model is also criticized for requiring unobservable values of assets and asset return volatility.

To the best of our knowledge, most empirical studies on banks apply market-based methods for default risk prediction (e.g. Gropp and Moerman, 2004; Gropp, Vesala and Vulpes, 2009; Blundell-Wignall and Roulet; 2012; Harada, Ito and Takahashi, 2013; Milne, 2014). The Merton default risk measure is also considered by the European Central Bank (2005) to be an important measure for providing early indications of financial fragility. A key benefit of the market-based default prediction models is also that these sorts of models are theoretical models for firm bankruptcy that do not require actual defaults or adjustments for different bankruptcy legislations, since default is defined as when the market value of assets are insufficient to cover the debt. This makes it possible to compare banks operating under different legislations. Furthermore, since our aim is to regress the probability of default against the Basel capital and liquidity ratios, we believe it could be problematic to perform a regression analysis where the dependent variable is obtained from accounting ratios and the independent variables themselves are accounting ratios. Due to the reasons stated above we choose to use a market-based model in our study, and thus we will devote the next section to the technical aspects of option pricing frameworks for default prediction.

2.3.2 Default prediction using option pricing theory

In this section we cover the specifications and logic behind the Merton model, different approaches of measuring the market value of assets and volatility of asset returns, i.e. the unobservable values of the model, and finally we present an overview of extended and simplified versions of the Merton model.

As previously mentioned, the Merton (1974) model applies the Black and Scholes (1973) formula for call option valuation to the context of the firm. Merton's equation for valuing equity as a standard European call option on the firm's assets is given in *Equation 5* below:

$$V_E = V_A N(d_1) - X e^{-r_f T} N(d_2) \tag{5}$$

where $N(.)$ is the cumulative density function of the standard normal distribution of d_1 and d_2, defined as

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r_f + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{6}$$

and

$$d_2 = d_1 - \sigma_A \sqrt{T} = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r_f - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \tag{7}$$

V_E is the market value of the firm's equity, V_A is the market value of total assets, which is assumed to follow a geometric Brownian motion, X is the face value of the firm's debt maturing at time T, r_f is the risk-free interest rate, σ_A is the annualized standard deviation of normally distributed assets returns. As previously explained, the firm is assumed to default if the value of assets, V_A, at time T is lower than the value of debt, X. The call option equation (*Equation 5*), can be interpreted as the present value of the expected payment under risk neutrality, where all assets are expected to grow at the risk-free rate.

In order to calculate default probabilities by using the Merton model, one has to decide on a level of debt that should represent the default point of the firm, as well as a time horizon for the option. Some researchers choose the book value of total debt as the default point (see Blundell-Wignall and Roulet, 2012), while others, such as Crosbie and Bohn (2003), argue that firms in general do not default when the value of assets falls below the value of total debt. The long-term nature of some debt gives the firms more time and allows for continued trade and service of the firm's debt. In line with the argumentation of Crosbie and Bohn, the KMV model suggests to set the default point somewhere between total debt and short-term debt. More specifically, KMV recommends the default point to be set equal to the total amount of short-term debt plus one half of the long-term debt. This method is commonly applied in studies on default prediction (see for example Vassalou and Xing, 2004; Gharghori et al., 2006; Bharath and Shumway, 2008; Campbell, Hilscher and Szilagyi, 2008). Moreover, Afik et al. (2016) performs an extensive comparative study of different variations of the Merton model and evaluate the accuracy of using different levels of long-term debt for the default point. It is found that adding between one tenth of the long-term debt and half of the long-term to the short-term debt gives the most accurate results for default prediction. Using levels within this range yield similar results. With regard to the time horizon, T is commonly assumed to be one year (Merton, 1973; Milne, 2014; Gharghori et al., 2006). However, Brockman and Turtle (2003) apply a 10-year horizon and argue that T does not directly represent the time to maturity of debt, but rather the lifespan of the firm. In contrast, Gharghori et al. (2006) argue that there are too many factors that may affect a firm's default probability if a time period longer than one year is chosen.

The next step required in order to use Merton's model for default prediction is to estimate values of V_A and σ_A, as all other variables in the model are directly observable. Three main approaches for estimating these two unobservable values can be found in previous literature, where the *Equation Approach* is most commonly used (Afik, Arad and Galil, 2016). The method was proposed by Jones, Mason and Rosenfeld (1984) and Ronn and Verma (1986).

As shown by Jones et al., the relation between the volatilities under the model assumptions is $\sigma_E = \frac{V_A}{V_E} \cdot \frac{\partial E}{\partial A} \sigma_A$ [5], and using Black and Scholes' (1973) model it can be shown that $\frac{\partial E}{\partial A} = N(d_1)$.

[5] $\frac{\partial E}{\partial A}$ is the partial derivate of the value of equity with respect to the value of the firm (Jones et al., 1984).

The relation between the equity volatility and the asset volatility can then be rewritten as:

$$\sigma_E = \frac{V_A}{V_E} N(d_1) \sigma_A \tag{8}$$

Using the *Equation Approach*, the two unknown variables, V_A and σ_A, are solved for simultaneously using the call option equation (*Equation 5*) and the relation between equity volatility and the asset volatility (*Equation 8*). The approach is employed by for example Hillegeist et al. (2004) and Campbell et al. (2008), but also commonly used in finance textbooks such as Hull (2012, p. 531).

Another approach for estimating V_A and σ_A is the *Iterative Approach* recommended by Moody's KMV. Studies employing this method are, for example, Vassalou and Xing (2004) and Gharghori et al. (2006), who use the equity volatility from one year's daily observations as an initial estimate for asset volatility. The estimated asset volatility is then used as input into the call option equation (*Equation 5*) to solve for daily asset values. The standard deviation of these asset values then becomes a new estimate for asset volatility and the process is repeated until the value of asset volatility converges to a precision of 0.0001. Noteworthy, the actual KMV approach to estimate asset volatility is more complex since it includes additional adjustments for country, industry and firm size (Crosbie and Bohn, 2003).

A third estimation approach is *Maximum Likelihood Estimation*, proposed by Duan (1994). Duan constructs a likelihood function based on a time series of observed equity values. The time series is treated as a sample of transformed data, where the call option equation (*Equation 5*), defines the transformation from implied asset values to the equity values. Due to this relation, the unknown asset values can be obtained through the likelihood function based on the known equity values. Studies employing this approach are for example Wong and Choi (2009), Ericsson and Reneby (2005), and Duffie, Saita and Wang (2007).

After deciding on a default point and time horizon, and after obtaining values of the two unobservable variables, the probability of default can be calculated as follows:

$$PD = 1 - N(d_2) = 1 - N\left(\frac{\ln\left(\frac{V_A}{X}\right) + \left(r_f - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}\right) \quad (9)$$

The probability is defined as the probability that the market value of assets, V_A, is lower than the face value of debt, X, at time T. The measure can be derived from d_2 in the call option equation, referred to as the distance-to-default, which can be interpreted as the normalized distance between the market value of the firm's assets and the face value of the debt.

In the original Merton model, assets are expected to grow at the risk-free rate. Studies using the risk-free rate are for example, Gropp et al. (2009) and Blundell-Wignall and Roulet (2012). However, in order to calculate real world probabilities of defaults, other studies (e.g. Vassalou and Xing (2004); Crosbie and Bohn, 2003; Duffie, Saita and Wang, 2007; Reisz and Perlich, 2007), use the expected asset returns, μ_A, instead of the risk-free rate, r_f, as the expected growth rate. Adjusting *Equation 9* above to consider real world probabilities instead of risk-neutral ones is easily done by replacing r_f with μ_A.

Even though the Merton model is still widely used in academic research, several variations of the model have emerged over the years. Most common has been to extend the model by considering additional aspects. Examples of such aspects are more complex debt structures (Geske, 1977), default points at values lower than the total debt level (Crosbie and Bohn, 2003), subordination arrangements and limits on refinancing (Black and Cox, 1976), corporate taxes and bankruptcy costs (Turnbull, 1979). Crosbie and Bohn (2003), Brockman and Turtle (2003) and Reisz and Perlich (2007) also diverge from the Merton standard option approach by suggesting that equity should be modelled using a barrier option pricing framework. More specifically, these studies view equity as a down-and-out call option where the company does not only default if the value of the firm's assets falls below debt at maturity, but also if it breaches a specified level, the barrier, before the maturity date. In contrast to the extensions of the Merton model, Bharath and Shumway (2008) introduce a simplified prediction model, "the naïve model", where market values of assets and asset return volatilities are assumed instead of solved for using one of the three main methods previously explained. In a comparative study of several variations of the Merton model, Afik et al. (2016) find the down-and-out call option (DOC) model to outperform all other variations of the Merton model evaluated in their study.

3. Motivation of thesis and hypothesis development

The Basel standards are under continuous development and in addition to the current tier 1 capital ratio, several new dimensions are introduced in Basel III in form of the Basel equity ratio and the two liquidity ratios; the liquidity coverage ratio and the net stable funding ratio. One of the main objectives of the Basel Accords is to limit future bank failures, and it is therefore important to assess whether the regulatory tools provided by the framework can be found to be directly associated with bank default risk. As Basel III is under implementation, there is limited research on the new ratios and their relevance. Blundell-Wignall and Roulet (2012) perform one of the more detailed studies within this field by assessing the association between the tier 1 capital ratio and the default risk measure distance-to-default. However, we identify four possible adjustments that can be made to the default risk measure in order to achieve results that better reflect reality. These adjustments are described below:

1. Blundell-Wignall and Roulet apply Merton's (1974) model, which views the firm's equity as a standard call option on the firm's assets. The model assumes that default occurs if the value of the firm's assets is lower than the value of the firm's debt at time *T*. However, we argue that this is an overly simplified construction of reality and consider it to be of greater interest to study the probability of default during the time period up until time *T*, and not only at time *T*. It is the firm's position during a period of time and not at a specific point in time that should be reflected in the risk measure.

2. The applied model has not been adjusted for cash outflows that affect the value of the firm's assets, more specifically dividend payouts and coupon payments. As these affect the value of the firm they should also be included in the default risk measure.

3. The estimated risk measure distance-to-default is calculated using a risk-free interest rate. However, we argue that using expected asset returns would better reflect reality.

4. We do not find the measure distance-to-default as intuitive as an actual probability of default and believe an analysis is better performed based on probabilities instead of how far away from default a firm is.

By reviewing previous research on default prediction we are able to identify methods that incorporate the aforementioned adjustments, and thus enable us to calculate a more accurate default risk measure than the one studied by Blundell-Wignall and Roulet. This approach enables us to test the relevance of the tier 1 capital ratio further. Additionally, we contribute to the research field by extending the assessment of the Basel Accord ratios through the inclusion of the three new ratios introduced in Basel III. Lastly, we study a longer time period than Blundell-Wignall and Roulet (2012), which we believe enables a more detailed analysis that also allows us to capture and analyze potential effects from the implementation of Basel III that started in 2013.

Previous findings oppose the view of BCBS that the Basel ratios are relevant tools in preventing bank failures. Blundell-Wignall and Roulet (2012), Milne (2014) and Flannery and Giacomini (2015) all find that the tier 1 capital ratio is not a significant measure when explaining changes in default probability and claim that the measure is overly complex. Hong et al. (2014) show that both the LCR and NSFR are of limited relevance when predicting bank failures. Evidently, the views on the effectiveness of the Basel ratios diverge. In line with the purpose of the Basel Accords we however formulate the first hypothesis as:

Hypothesis 1: Higher Basel III ratios (the tier 1 capital ratio, the Basel equity ratio, the liquidity coverage ratio and the net stable funding ratio) are associated with lower probabilities of bank default.

In regard to the capital ratios, previous research argue that the tier 1 capital ratio is overly complex and finds that the regular equity ratio is a better predictor of default risk. Since the Basel equity ratio is similar to the regular equity ratio we state the second hypothesis as:

Hypothesis 2: The Basel equity ratio has a more significant negative impact on the probability of default than the tier 1 capital ratio.

4. Data

The data used in our study is mainly collected from Thomson Reuters Datastream, a global financial and macroeconomic database covering equities, stock market indices, currencies, company fundamentals, fixed income securities and key economic indicators for 175 countries and 60 markets. Even though a larger sample could possibly have been obtained by combining data from different sources we prefer to use one data provider that defines and assesses the data uniformly.

Our initial sample consists of 1,313 European banks and 1,251 US banks, and the sample includes both active and failed banks. However, we limit the sample by only including banks with either a market capitalization of more than USD 2 billion at the end of 2006 or an average market capitalization of more than USD 2 billion during the period 2006 to 2015. This twofold assessment is carried out in order to include both large banks that have bankrupted since 2006 as well as large banks that have recently become listed. The USD 2 billion level is chosen for the US banks as this is the lower limit for mid-cap companies in the US, and the same limit is applied to the European banks to achieve a comparable sample. Both European and US banks are included in the sample since the Basel standards are applicable in both regions. This regional choice also makes the study comparable to previous studies within the field. Furthermore, our sample period ranges from December 31 in 2006 to December 31 in 2015 in order to facilitate an analysis over a complete economic cycle, and allowing for analysis of the implementation of Basel III starting in 2013. Finally, we omit those banks that are lacking the data necessary for the calculations of probability of default. After the above mentioned limitations we obtain a final sample of 145 banks.

We have chosen not to winsorize the data as this could lead to observations containing relevant information being omitted. Instead, outliers are manually assessed in order to determine the reliability of those data points. We deem it important to keep outliers since information can also be contained in the tails of the sample. Extreme values have been compared with the annual financial statements and replaced if Datastream has reported a different value than the annual report.

Descriptive statistics of the data sample are presented in *Table 1*. Out of the 145 banks, 93 are European banks and 52 are US banks. The average European bank is smaller than the average US bank, in regard to market capitalization. In regard to asset values, the average European bank reported higher asset values than the average US bank in our sample. Notably, differences between US GAAP and IFRS accounting standards make US banks look smaller than they would under IFRS accounting (Flannery and Giacomini, 2015)[6]. A list of all banks included in the sample together with the market capitalization for each bank can be found in *Table A1* in Appendix.

Table 1. Descriptive statistics of data sample

(USD bn)	Total sample	Europe	US
Number of banks	145	93	52
Market cap 2006:			
Average	29.00	27.63	30.43
Max	274.00	210.86	273.69
Min	1.00	1.56	0.91
Market cap 2006-2015:			
Average	20.62	19.50	22.56
Max	283.44	210.86	283.44
Min	0.05	0.05	0.73
Total assets 2006-2015:			
Average	358.76	424.94	244.00
Max	3777.00	3777.00	2573.00
Min	4.59	8.46	5.00

This table shows descriptive statistics for our data sample. In total 145 individual banks are included in the sample, of which 93 are European banks and 52 are US banks.

[6] The main cause for the size difference is that IFRS netting conditions is stricter than US GAAP, meaning that under IFRS the gross replacement value of derivatives is shown on the balance sheet, whilst this is not the case under US GAAP (D'Hulster, 2009, cited in Flannery and Giacomini, 2015).

5. Method

In the following section we describe our method, beginning with the chosen model for default prediction, the DOC model. We then describe the model inputs together with any assumptions made in order to calculate annual default probabilities for all banks over the sample period. Thereafter we present the regression model used to assess the association between the calculated default measures and the Basel ratios.

5.1 The DOC model

To calculate a default risk measure that considers the possibility that default can occur at any point in time we choose to model equity as a barrier option, more specifically a down-and-out call option (DOC). Our choice of model is also supported by the study of Afik et al. (2016) that finds the DOC model to outperform most variations of the Merton model. Notably, there are other aspects of reality that could be taken into consideration, e.g. bankruptcy costs. However, we do not adjust for bankruptcy costs since previous research has shown that bankruptcy costs are not likely to alter the qualitative results of a structural model, such as the DOC model (Black and Cox, 1976). The DOC model is described by Brockman and Turtle (2003) and employed by for example Gharghori et al. (2006) and Reisz and Perlich (2007).

5.1.1 Model specifications

In the DOC model, default is assumed to occur if the asset value, V_A, falls below the value of debt, X, at maturity, or if the value of V_A falls below a pre-specified level, referred to as the barrier, B, before the maturity date. Breaching the barrier can be interpreted as breaching a debt covenant, and as long as the value of the firm's assets is above the barrier, creditors cannot force dissolution. The barrier can be set equal to, above, or below the strike price of the option, but has to be below the initial market value of assets, since the option otherwise has no value (Brockman and Turtle, 2003). For the DOC equation and the probability of default, we have applied the formulas presented by Reisz and Perlich (2007), as we find their presentation to be the most comprehensive. The formulas also include dividend and coupon payments. For the derivation of the formulas, please see the original paper.

When using the DOC model, it is assumed that the value of assets follows a geometric Brownian motion:

$$dV_A(s) = (\mu_A - \delta)V_A(s)ds + \sigma_A V_A(s)dW(s) \tag{10}$$

where μ_A is the drift of the asset return process, σ_A the volatility coefficient, δ the payout ratio to security holders (both shareholders and debtholders), $V_A(s)$ is the asset value at time s, and $dW(s)$ is the standard Wiener process (Reisz and Perlich, 2007).

Depending on the chosen level of B, there are two different valuation formulas for calculating the value of the down-and-out call option, one that is used when $B < X$ and one when $B \geq X$. Below we present the version where $B \geq X$ as this is the case for our study[7]:

$$V_E = V_A e^{-\delta T} N(d_1) - X e^{-r_f T} N(d_1 - \sigma_A\sqrt{T}) - \left[V_A e^{-\delta T} \left(\frac{B}{V_A}\right)^{\frac{2(r_f-\delta)}{\sigma_A^2}+1} N(d_1^B) - X e^{-r_f T} \left(\frac{B}{V_A}\right)^{\frac{2(r_f-\delta)}{\sigma_A^2}-1} N(d_1^B - \sigma_A\sqrt{T}) \right] \tag{11}$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{B}\right) + \left(r_f - \delta + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad \text{for } B \geq X \tag{12}$$

and

$$d_1^B = \frac{\ln\left(\frac{B}{V_A}\right) + \left(r_f - \delta + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \quad \text{for } B \geq X \tag{13}$$

The first two terms of *Equation 11* can be recognized from the valuation of a standard call option of the firm's assets, since it compares the expected value of assets and the present value of the future debt repayment. The two terms within brackets represent the loss in equity value that would occur if the value of assets breaches the barrier before the maturity date, T. Assets are expected to grow at the risk-free rate, r_f, less the payout ratio, δ.

[7] For the scenario where $B < X$, please see Gharghori et. al (2006) or Reisz and Perlich (2007).

Similar to the standard option model, the values of V_A and σ_A are unobservable also in the DOC model. To be able to solve for the two unknowns, the DOC equation needs to satisfy below relation between the asset and equity volatilities:

$$\sigma_E = \frac{V_A}{V_E} \Delta_{Barrier} \sigma_A \tag{14}$$

where

$$\Delta_{Barrier} = \frac{\partial V_E}{\partial V_A} = e^{-\delta T} N(d_1) + \left(\frac{B}{V_A}\right)^{\frac{2(r_f - \delta)}{\sigma_A^2} - 1} \left\{ \frac{X e^{-r_f T}}{V_A} N\left(d_1^B - \sigma_A \sqrt{T}\right) + \right.$$

$$\left. \left(\frac{2(r_f - \delta)}{\sigma_A^2}\right) \left[\frac{B^2 e^{-\delta T}}{V_A^2} N(d_1^B) - \frac{F e^{-r_f T}}{V_A} N\left(d_1^B - \sigma_A \sqrt{T}\right) \right] \right\} \tag{15}$$

We estimate V_A and σ_A for each bank by simultaneously solving for the values using the *Equation Approach* previously presented in this paper. Apart from being the most common approach for solving for V_A and σ_A, the method is chosen for its relative simplicity. We set the call option equation of the DOC model (*Equation 11*) and the volatility relation equation, (*Equation 14)*, equal to zero by first deducting V_E from *Equation 11* and σ_E from *Equation 14*, and then using Excel Solver to simultaneously change the values of V_A and σ_A until both *Equation 11* and *14* equal zero.

In order to cover the third aspect not included in Blundell-Wignall and Roulet's (2012) study, we adjust the default risk measure to better reflect real world probabilities instead of risk-neutral probabilities. In order to do so we replace the risk-free rate, r_f, in the probability function with the expected return on assets, μ_A. This adjustment is performed since μ_A better reflects that assets are managed at a changing interest rate (Harada et al., 2013). Reisz and Perlich (2007) also replace r_f with μ_A and use the below formula to calculate the probability of default when $B \geq X$:

$$PD = 1 - N\left(\frac{\ln\left(\frac{V_A}{B}\right) + \left(\mu_A - \delta - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \right) + \left(\frac{B}{V_A}\right)^{\frac{2(\mu_A - \delta)}{\sigma_A^2} - 1} N\left(\frac{\ln\left(\frac{B}{V_A}\right) + \left(\mu_A - \delta - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \right) \tag{16}$$

The first term of the probability function, *1-N(.)*, can be interpreted in the same way as the default probability of a standard option, i.e. the probability that the value of assets falls below the default point, *X*, at time *T*. However, in this case, the default point is represented by the barrier, a point above or equal to the debt level, and therefore, V_A/X in the standard option equation is replaced by V_A/B. The second term is an additional component of default risk due to the barrier, and reflects the probability that V_A falls below B before the maturity date.

Using this DOC model, we would expect to receive higher probabilities of default when the current market value of assets, V_A, is low relative the barrier, B, when the asset volatility, σ_A, is high, and when the expected asset growth (μ_A - δ) is low.

5.1.2 Model inputs

All inputs to the call option equation (*Equation 11*) and the volatility relation equation (*Equation 14*) are computed as described below:

- The market value of equity, V_E, is measured as the market value of equity on the last trading day of each year in the sample period.
- The volatility of equity, σ_E, is calculated as the annualized standard deviation of the prior year's daily stock returns[8]. More specifically, we have calculated daily standard deviations of the stock returns for each bank and multiplied it with $\sqrt{251}$ to achieve the annualized standard deviation. 251 is assumed to be the average number of trading days each year.
- The strike price of the option, X, is set to the amount of debt maturing at time T and represents one type of debt. We choose to employ the KMV approach, where X is set equal to short-term debt plus half of the long-term debt since that is the most commonly used approach. The reasoning behind this level is that firms usually do not default when the asset value falls below the value of total debt, but at a point lower than that since the long-term nature of some debt gives the firms more time, and allows for continued trade and service of the firm's debt (Crosbie and Bohn, 2003). Furthermore, we do not find any reason for not using the KMV approach since Afik et al. (2016) show that a default point representing short-term debt plus a level between one tenth and half of the long-term debt gives more accurate probabilities of default than using only short term debt or total debt.
- rf is the risk-free interest rate, collected from OECD for each country. The rates are based on three-month Treasury bill rates. For four countries (Croatia, Cyprus, Lithuania and

[8] As pointed out by Afik et al. (2016), a forward-looking implied volatility would probably be a more suitable choice, but since this is not available for many firms we use historical volatility for the estimation of equity volatility.

Turkey) OECD do not provide numbers and we therefore assume a constant risk-free interest rate of 2% for those countries.

- T is the maturity date of the option. For standard call options T is usually set to one year, assuming that all debt is repayable after one year. Brockman and Turtle (2003) argue that the maturity of a DOC option represents the firm's lifespan and set T to ten years, also assuming that all debt matures after 10 years. However, in line with Gharghori et al. (2006) we choose to interpret T as the date of debt maturity, and not as the lifespan of the firm, since there are too many factors that may affect a firm's default probability if a time period longer than one year is chosen. Thus, we set T equal to one year.
- The barrier, B, is the pre-specified level to which the value of assets is not allowed to fall during the time period. If the barrier is breached during time T, the firm defaults. The barrier can be set equal to, above, or below the strike price, X, of the option, but has to be below the initial market value of assets, V_A (Brockman and Turtle, 2003). Prior research, e.g. Gharghori et al. (2006) and Brockman and Turtle (2003), sometimes back out implied values of the barrier by assuming values of V_A and σ_A. However, to our knowledge no analysis of implied barriers for banks have been performed, and we therefore choose a barrier equal to the strike price, i.e. $B=X$.
- The payout rate, δ, is calculated as the total dividend and interest payments during the prior year divided by the implied market value of assets.

In order to be able to calculate the probability of default, PD, we compute the expected asset return, μ_A, by using the capital asset pricing model, CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966):

$$\mu_A = r_f + \beta_A(r_m - r_f) \tag{17}$$

We acknowledge that other methods would also be possible, for example Campbell et al. (2008) use a constant market risk premium of 6% and calculate the expected asset return as $\mu_A = r_f + 0.06$. However, we believe that variations in asset beta should be incorporated in the measure and therefore consider CAPM to be a better estimate of the expected asset return. This is in line with for example Afik. et al. (2016) that also use the CAPM approach. The risk-free rate, r_f, is the rate obtained from OECD. To calculate the asset beta, $ß_A$, we first calculate the equity beta, $ß_E$, using daily returns for the firm specific stocks and the market indices, MSCI Europe for the

European banks and S&P500 for the US banks[9]. To achieve the equity betas for each firm the covariance between the stock returns and the market returns are divided with the variance of the market return for each year. We find our betas to be close to 1, which seems reasonable for large international banks. The relation $\beta_A = \beta_E \cdot \frac{\sigma_A}{\sigma_E}$ is then used to calculate asset betas [10], where σ_A and σ_E are the same as the inputs used in the option pricing model. Finally, the last input needed for calculating μ_A is the market risk premium, which is assumed to be 5% for all banks in the sample[11].

Finally, by using the probability function (*Equation 16*) we obtain annual bank specific probabilities of default that are adjusted for the aspects not included in Blundell-Wignall and Roulet's (2012) model. The *PD*s incorporate default risk over time, dividend and coupon payments, as well as expected asset returns.

5.2 The regression model

In order to measure if, and to what extent, the Basel ratios can explain the probability of default for the banks in our sample, we perform a panel data analysis, where the regression model includes the probability of default as the dependent variable and the Basel ratios together with additional control variables as the independent variables.

5.2.1 Model specifications

We choose to perform a panel data regression since we believe that there are omitted variables, which we are unable to control for that are likely correlated with the variables in the model. Moreover, we choose a fixed effects regression model rather than a random effects regression model as this is in line with previous research such as Blundell-Wignall and Roulet (2012) and Flannery and Giacomini (2015). Furthermore, a Hausman (1978) test is performed on our regression variables to further justify the decision to use a fixed effects regression. The results

[9] The MSCI Europe Index captures 446 constituents, including both large and mid-cap companies across 15 developed markets countries in Europe. S&P 500 covers the 500 largest American companies listed on the NYSE or NASDAQ.

[10] The relation is used by Afik et al. (2016) and derived from the expression of a Black-Scholes call beta $\beta_E = \frac{A}{E} \cdot N(d_1) \cdot \beta_A$ where the call option and the underlying is replaced by the equity and the assets respectively. Thereafter, the volatility relation (*Equation 8*) is used to replace $\frac{A}{E} \cdot N(d_1)$ by the volatilities ratio $\frac{\sigma_E}{\sigma_A}$.

[11] The market risk premium of 5% is based on the results from the study by Fernandez, Linares & Fernandez Acin (2014), in which the US and most European countries have been found to have a market risk premium of approximately 5-6%.

from the test can be found in *Table A2* in Appendix, and indicate that fixed effects are preferable over random effects.

Ideally, one would follow the same banks across the whole sample period, but we have chosen to use an unbalanced data set since we believe that the observations from the banks that failed during the sample period contain valuable information for our study. However, a panel data regression model allows for an unbalanced sample, and the mechanics behind an unbalanced panel regression is not much different from a balanced one. Time demeaning is done for all available observations, meaning that the mean value of each variable for each bank over the sample period is subtracted from each available observation for that same variable and bank (Wooldridge, 2006, p.488). The panel data regression model can be written as follows (Wooldridge, 2006, p.482):

$$\ddot{y}_i = \beta_0 + \beta_1 \ddot{x}_{i1} + \cdots + \beta_k \ddot{x}_{ik} + \ddot{u}_i \tag{18}$$

where

$\ddot{y}_i = The\ time - demeaned\ dependent\ variable$

$\beta_0 =$ *The intercept of the dependent variable*

$\beta_k = The\ coefficient\ of\ the\ independent\ variable$

$\ddot{x}_i = The\ time - demeaned\ independent\ variable$

$\ddot{u}_i = The\ time - demeaned\ error - term$

$k = The\ number\ of\ independent\ variables$

$i\ = observation\ number$

Using the regression model on the previous page for the purpose of our study, we regress the probability of default against the four Basel ratios as well as three additional control variables; size, return on equity and annual house price changes. Further information on the model inputs as well as motivations for the control variables are presented in the next section. Our main regression model is defined as follows:

$$PD_i = \beta_0 + \beta_1 T1CR_i + \beta_2 B\_ER_i + \beta_3 LCR_i + \beta_4 NSFR_i + \beta_5 \mathrm{LN\_MV}_i + \beta_6 ROE_i + \beta_7 HOUSE\_IND_i + \sum \beta_8 YEAR_i + \ddot{u}_i$$

where *PD* is the probability of default, *T1CR* is the tier 1 capital ratio, *B_ER* is the Basel equity ratio, *LCR* is the liquidity coverage ratio, *NSFR* is the net stable funding ratio, *LN_MV* is the size variable, *ROE* is the return on equity and *HOUSE_IND* is the annual change in house prices. The variable *YEAR* represent dummy variables for the years 2006 to 2015, and *ü* is the error term.

5.2.2 Model inputs

Below we specify the computation of the variables included in our model, as well as our expectations for the regression results.

- *PD* is the probability of default, obtained using the DOC model presented in this paper.
- *T1CR*, is the tier 1 capital ratio as reported by Datastream, representing tier 1 capital divided by risk-weighted assets. In line with the purpose of the Basel ratio, we expect a negative association between *T1CR* and *PD* since a high *T1CR* should correspond to a higher level of capital that can be used as a buffer to protect against unexpected losses under a stressed scenario. The same argumentation is used by Blundell-Wignall and Roulet (2012) who find the *T1CR* to have a negative, but insignificant, impact on the probability of default. Since our adjustments to the *PD* measure involves non-linear transformations of Blundell-Wignall and Roulet’s dependent variable, we expect to achieve a similar but not necessarily identical relation.
- *B_ER*, the Basel equity ratio**,** represents the Basel leverage ratio. However, for the sake of simplicity we choose to refer to this regulatory tool as an equity ratio since it focuses on the equity level of the bank, and it could otherwise be misinterpreted as the regular leverage ratio used in business analysis (focusing on the firm’s debt). Since banks only started to report the Basel equity ratio in 2015, we are not able to obtain reported ratios

from Datastream, and therefore we calculate *B_ER* as tier 1 capital divided by the book value of total assets. According to the definition of the ratio in Basel III, total assets should be adjusted for off-balance sheet items, but since these are not available for banks in Datastream we are not able to perform this adjustment. In line with the reasoning for the tier 1 capital ratio, we expect *B_ER* to have a negative association with *PD* since a higher level of tier 1 capital should decrease the probability of default as the capital can be used as a buffer during periods of stress.

- *LCR*, is the liquidity coverage ratio, calculated as cash and securities divided by total deposits. The implementation of the ratio started in 2015, meaning that banks have not presented any values of the ratio prior to 2015. According to the Basel definition of the ratio, high quality liquid assets should be divided by total net liquidity outflows over the next 30 days, under a stressed scenario. Ideally, we would aim to calculate the measure in accordance with the definition, but since banks neither report what is to be considered highly liquid assets, nor their near-term net liquidity outflow this is not possible. As shown by Hong et al. (2014), calculating the *LCR* without this information directly available, is highly complex and involves multiple assumptions. Therefore, we consider such a calculation to be outside the scope of this paper and choose to use cash and securities divided by total deposits as a proxy variable for the *LCR*. Cash and securities can be viewed as highly liquid assets and the deposits represent the liquidity outflow aspect, as customers can be expected to withdraw from their deposits with the banks under a stressed scenario. Since the Basel Accords aim to prevent bank defaults we believe that the *LCR* proxy will be negatively associated with *PD*. Moreover, the minimum requirement for the *LCR* is 100%, implying that a high *LCR* lowers the risk of default (BCBS, 2011).
- *NSFR*, is the net stable funding ratio, calculated as the sum of equity and long-term interest-bearing debt divided by total loans. Basel III defines the ratio as available amount of stable funding divided by required amount of stable funding, i.e. sources of funding divided by uses of funding. Long-term interest-bearing debt and equity is considered to be sources of funding, while loans to consumers and companies are viewed as uses of funding. To achieve a final ratio, the different types of assets and liabilities are assigned different weights. Since banks have not yet started to report the ratio[12] and since there is not sufficient information in the financial statements for us to calculate an accurate *NSFR*,

[12] The *NSFR* minimum requirement will be presented in 2018 and banks will thereafter start to report the ratio.

we use the sum of equity and long-term interest-bearing debt divided by total loans as a proxy to capture the relation between sources and uses of funding. Hong et al. (2014) find the *NSFR* to have a small but significant negative association with the default risk measure. In addition, BCBS encourages a high *NSFR*, and we therefore expect our *NSFR* measure to have a negative impact on the probability of default (BCBS, 2011).

- Size, *LN_MV*, is calculated as the natural logarithm of the market value of equity and included in the model as a control variable. A size variable is used by for example Flannery and Giacomini (2015) who applies the natural logarithm of the book value of assets. However, we choose market value of equity as our size variable since it both controls for size differences and reflects the market's future expectations of the bank's performance. We expect the association between size and *PD* to be negative, the larger the bank is, the lower is the probability of default. This relation is also discussed by Hong et al. (2014), referring to the too-big-to fail problem, where large banks usually have lower default probability as they commonly receive government support if the default risk is large.

- House price index, *HOUSE_IND*, is obtained from OECD for all countries apart from Croatia, Cyprus and Poland for which we obtain the data from Datastream. The annual change in the house price indices is used as a control variable, and similar to Blundell-Wignall and Roulet (2012) we expect the measure to capture credit cycles that drives asset values in each country. Increasing house prices is thus expected to be negatively associated with the probability of default.

- Return on equity, *ROE*, is net income divided by the average of the previous year's and the current year's common equity. Blundell-Wignall and Roulet (2012) do not include any profitability measure in their regression model, but when examining previous research on default prediction we find that models often include a profitability measure to explain the probability of default. For example, accounting-based models such as Altman (1968) and Skogsvik (1988) use earnings before interest and taxes divided by total assets as profitability measure in their default prediction models. Additionally, Flannery and Giacomini (2015) also include *ROE* in their regression analysis of their market-based default risk measure. We choose to also control for bank profitability in our model and in line with previous research we expect banks with higher *ROE*, i.e. banks with higher profitability, to be safer than banks with lower *ROE*. Hence, we expect a negative association between *ROE* and *PD*.

- Year dummies are included since we believe there are variations in *PD* that are associated with certain years that we cannot control for otherwise. More specifically, we do not want the financial crisis to affect the relations between the Basel ratios and the probability of default.

In addition to the above variables included in our main regression model, we also compute the regular equity ratio, *ER*, which is the book value of equity divided by the book value of total assets. This measure is included in order to be able to compare our results with those of Blundell-Wignall and Roulet (2012) as they use an inversed equity ratio instead of the Basel equity ratio, where they divide total assets with equity. We do not include *ER* in our main regression model, but perform an additional regression analysis where we replace the Basel equity ratio with the regular equity ratio to see how the results are affected. In line with Blundell-Wignall and Roulet and the reasoning behind our Basel equity ratio, we expect the regular equity ratio to also be negatively associated with *PD*, i.e. a high *ER* should decrease the default risk.

In *Table 2* below we summarize the definitions, calculations and expected signs for all independent variables.

Table 2. Definitions of independent variables

Variable name	Acronym	Definition	Expected sign
Tier 1 capital ratio	T1CR	$\frac{tier\ 1\ capital}{risk-weighted\ assets}$	(-)
Basel equity ratio	B_ER	$\frac{tier\ 1\ capital}{total\ assets}$	(-)
Liquidity coverage ratio	LCR	$\frac{cash\ and\ securities}{total\ deposits}$	(-)
Net stable funding ratio	NSFR	$\frac{equity\ and\ LTD}{total\ loans}$	(-)
Logarithm of market value of equity	LN_MV	*ln(market value of equity)*	(-)
Return on equity	ROE	$\frac{net\ income}{average\ shareholder's\ equity}$	(-)
House index	HOUSE_IND	*The annual real return of country specific house indices*	(-)
Year	YEAR	*One dummy for each year 2006-2015*	(+/-)
Equity ratio	ER	$\frac{bookvalue\ of\ equity}{total\ assets}$	(-)

This table shows the definitions of the independent variables included in our regression model, as well as the expected signs of the respective coefficients.

6. Results and analysis

In this section we first present descriptive statistics of the inputs used for the estimation of asset values and asset return volatilities, as well as the obtained measures of these two unobservable variables. Thereafter we present the development of the default risk measure *PD* over the sample period. We then study the development of the tier 1 capital ratio and the Basel equity ratio over the sample period to thereafter compare levels of the four Basel ratios for two groups of banks; banks with low *PD*s and banks with high *PD*s. Subsequently, we continue with presenting the results from our regression analysis, both univariate and multivariate regressions, investigating the associations between the Basel ratios and *PD*. Lastly we perform an additional analysis of the differences between the Basel equity ratio and the regular equity ratio, as well as robustness tests to enable for further interpretation of the regression results.

6.1 Descriptive statistics of the probability of default

In order to provide some context to the computation of the *PD* measure, *Table 3* below presents summary statistics for the observable and estimated variables used in the DOC model. Average book value of assets, BV_A, for the whole sample is USD 358.76 billion and average book value of equity, BV_E, is USD 20.11 billion. Our estimated asset volatilities are constantly lower than the observed equity volatilities, where asset volatilities ranges from 0.06% to 27.47% and equity volatilities from 4.67% to 232.70 %. The payout ratio is on average 1.42% for our sample banks and estimated asset returns are on average 2.30%. Our estimated market values of assets are on average lower than the book value of assets, but the ratio ranges from 59.31% to 142.73%.

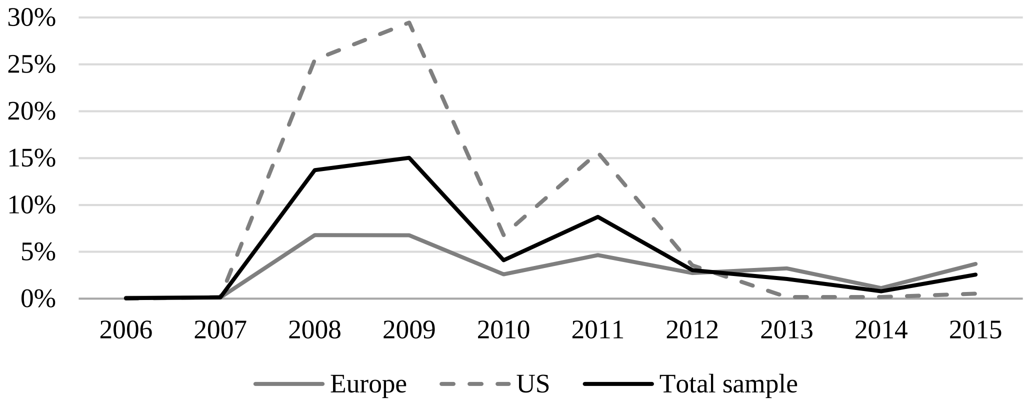
Table 3. Actual and estimated values for DOC model

	Number of obs.	Mean	Median	Max	Min	Std. Dev.
BV_A	1304	358.76	67.61	3777.00	4.59	629.72
BV_E	1304	20.11	5.42	233.93	0.34	36.00
V_E	1304	20.62	6.12	283.44	0.05	36.72
X and B (X=B)	1304	316.63	56.45	3508.80	3.86	570.50
σ_E (%)	1304	37.91	31.03	232.70	4.67	24.26
δ (%)	1304	1.42	0.74	10.59	0.00	1.64
μ_A (%)	1304	2.30	1.43	14.80	0.00	2.04
V_A	1304	333.55	64.15	3521.23	4.83	590.69
σ_A (%)	1304	3.67	2.81	27.47	0.06	2.95
V_A / BV_A (%)	1304	95.29	94.53	142.73	59.31	9.13
BV_E / BV_A (%)	1304	8.20	7.82	32.80	0.83	3.79
V_E / BV_A (%)	1304	11.13	9.36	57.54	0.02	8.29
V_E / BV_E (%)	1304	132.92	117.44	730.83	0.32	77.17
V_E / V_A (%)	1304	11.22	10.16	40.31	0.02	7.27

This table shows summary statistics for actual and estimated inputs for the down-and-out call option model. BV_A is the book value of assets, BV_E is book value of equity, V_E market value of equity and X is the face value of debt, set to the book value of debt. B is the barrier, set equal to X. σ_E is annualized standard deviation of equity returns, δ is the actual dividend payment and coupon payment divided by the estimated market value of assets, μ_A is the expected annual asset return. V_A is the estimated market value of assets and σ_A is the annualized volatility of the estimated market value of assets. Unless otherwise stated, all values are expressed in USD bn.

From the variables presented in *Table 3* on the previous page we are able to calculate probabilities of default for all sample banks. The development of the average *PD* for the period 2006 to 2015 is illustrated in *Figure 1* below. Both the development of average *PD* for the whole sample and for Europe and the US respectively are illustrated.

Figure 1. Average PD 2006-2015



This figure shows average *PD* for the years 2006-2015. The results are presented for the total sample of 145 banks, as well as for the 93 European banks and the 52 US banks respectively.

As shown in *Figure 1, PD* in year 2006 and 2007 is close to zero percent, but increases during the years of the financial crisis, starting in 2008. The average *PD* for the whole sample peaks in 2009 at 15%. Thereafter the default risk decreases in 2010, but increases again in 2011. After 2011, *PD*s are at lower levels again. The same development is seen in both Europe and the US, however, comparing European banks to US banks, the US constantly show higher average *PD*s than Europe, which drives the sample average *PD* upwards. After 2012, a shift occurs and US banks show slightly lower average *PD*s than European ones. The highest average *PD* can be seen in 2009 in the US, reaching almost 30%.

Notably, the median *PD* for both the sample and the two subsamples are lower than the average *PD* for all years, which can be explained by banks with high *PD* driving the mean value upwards. The highest individually recorded *PD* is as high as 89.5%. Detailed statistics over mean, median, maximum, minimum and standard deviation can be found in *Table A3* in Appendix, both for the total sample and for Europe and the US respectively. The overall development of *PD* is in line with what could be expected due to the disturbances in the financial markets during the recent financial crisis. Comparing our result with previous research, they are in line with the findings of Blundell-Wignall and Roulet (2012) and Milne

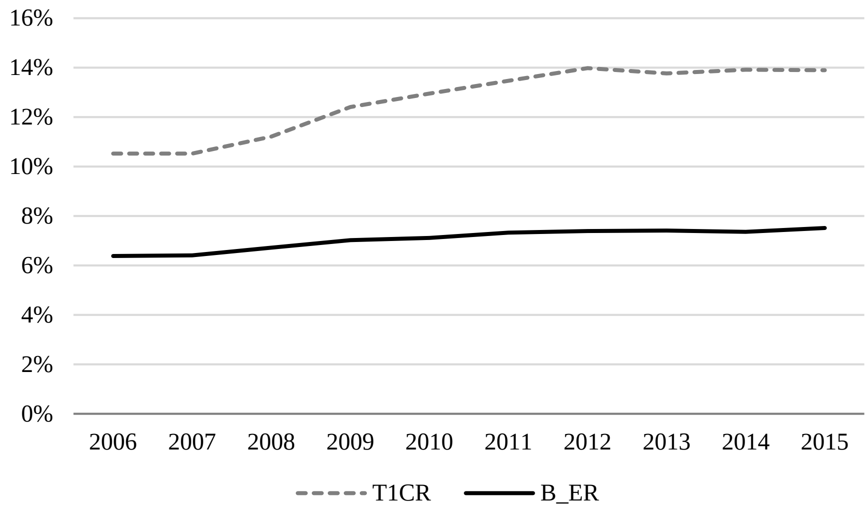
(2014) as they find that the distance-to-default decreases during the same years for which we see an increase in *PD*. A decrease in their measure distance-to-default, is equivalent to increased default risk.

6.2 Descriptive statistics of the Basel ratios

In this section we first study the development of actual levels of the two capital ratios of the Basel Accords in more detail, namely the tier 1 capital ratio and the Basel equity ratio. The first ratio has been subject to discussion due to the allowance of internal models for calculating the risk weights and the *B_ER* has been introduced as a complement to the *T1CR*. We choose to exclude *LCR* and *NSFR* from this initial comparison as our measures are only proxies, that even though they aim to capture the same aspects as the actual *LCR* and *NSFR*, they are not deemed useful for comparing actual levels of the Basel ratios.

In *Figure 2* below we present the development of the average tier 1 capital ratio and the average Basel equity ratio over the years 2006 to 2015 for the total sample. The first measure is affected by risk-weights and the second is not. A regional split that follows the same trend can be found in *Figure A1 and A2* in Appendix.

Figure 2. Average T1CR and B_ER 2006-2015



This table illustrates the average tier 1 capital ratio (*T1CR*) and the Basel equity ratio (*B_ER*) over the years 2006-2015 for the whole sample of 145 banks.

As shown in *Figure* 2 on the previous page the average tier 1 capital ratio for the whole sample has continuously increased since 2006, from just above 10% in 2006 to 14% in 2015. The increase was particularly evident during the years 2008 and 2009. The same trend holds for the Basel equity ratio, however the increase is not as distinct, increasing from roughly 6% to slightly more than 7% in 2015.

We continue with comparing actual levels of the Basel ratios between the lowest and highest quartile of estimated bank *PD*s. In other words, the ratios from the observations with the lowest 25% of *PD*s are compared to the ratios of the observations with the highest 25% of *PD*s. We first present mean values for the whole sample and then a division between Europe and the US. In addition, we also include a division between observations before and after Basel III started being implemented in 2013, which aims to capture any differences in the tier 1 capital ratio and the Basel equity ratio due to the new definition of tier 1 capital and the amendments in the approaches to calculate risk-weighted assets. Descriptive statistics from the comparisons are found in *Table 4* below.

Table 4. Average Basel ratios for banks with lowest and highest probability of default

		T1CR		B_ER		LCR		NSFR	
		low PD	high PD	low PD	high PD	low PD	high PD	low PD	high PD
Total		0.132	0.120	0.071	0.071	0.608	0.680	0.371	0.331
Region	Europe	0.127	0.128	0.058	0.055	0.706	0.863	0.378	0.309
	US	0.140	0.114	0.091	0.087	0.449	0.462	0.360	0.356
Time	Before Basel III	0.117	0.120	0.069	0.071	-	-	-	-
	After Basel III	0.160	0.125	0.075	0.071				

This table presents average Basel ratios for banks belonging to the first quartile (lowest) and the fourth quartile (highest) in regards to *PD* for the time period 2006-2015. The results are presented for the total sample, by region, before and after implementation of Basel III.

As seen in *Table 4*, low *PD* banks report higher tier 1 capital ratios than high *PD* banks when the whole sample is analyzed. The same pattern holds for the US, however, in Europe there is no clear difference between low and high *PD* banks. Before the implementation of Basel III started in 2013, low risk banks had an average tier 1 capital ratio that was lower than the ratio for risky banks, while the opposite relation is found after 2013. In regards to the Basel equity ratio banks with low *PD* show higher ratios. Comparing the Basel equity ratio before and after 2013, the low *PD* banks show higher ratios after 2013, while high *PD* banks have remained at the same ratio level. The *LCR* is lower for safe banks with lower default probability when the whole sample is assessed as well as when the comparison is made between Europe and the US. With regard to the *NSFR*, risky banks show lower ratios regardless of how the ratios are compared.

Concluding the results from the comparison between low and high *PD* banks, the results indicate that banks with low default risk most often have higher tier 1 capital ratios, Basel equity ratios and net stable funding ratios. This relation is in line with our expectations for the association tests of the ratios. In contrast, the liquidity coverage ratio is more often lower for banks with low *PD* than banks with high *PD*. This relation between *LCR* and low and high *PD* banks is not what we expected and indicates the opposite relation for the association tests, meaning that a high liquidity coverage ratio should increase the probability of default. However, this is a simple analysis that does not consider cross-section and time fixed effects or control for additional independent variables that could affect the results.

6.3 Regression results

In order to assess the association between the Basel ratios and the probability of default we first present results of the univariate panel data regressions and then the results of the multivariate panel data regressions for each variable, where we control for size, return on equity and changes in house prices. Thereafter we present the results of our main regression model including all Basel ratios and the additional control variables. Variations of the main regression model are also presented, using different combinations of independent variables.

6.3.1 Unexpected associations with *PD* - univariate regression results

The univariate regressions in *Table 5* below present an initial view of the associations between each of the independent variables and the probability of default, *PD*. In line with the purpose of the Basel Accords, all Basel variables are expected to have a negative impact on *PD*, meaning that higher capital and liquidity ratios should decrease the default risk. Contrary to what we expected, our univariate regression results show positive but insignificant associations between the Basel ratios and *PD*. However, this is prior to any inclusion of additional control variables, which may change the associations and significance levels. Notably, all of the additional control variables are significant at the 1% level and have the expected signs on their respective coefficients. This is also the case for our additional variable, *ER*, included for comparative purposes.

Table 5. The determinants of probability of default: Univariate regressions

Constant	T1CR	B_ER	LCR	NSFR	ER	LN_MV	ROE	HOUSE_IND
-0.019 (0.015)	0.185 (0.127)	–	–	–	–	–	–	–
-0.040* (0.023)	–	0.635 (0.343)	–	–	–	–	–	–
-0.007 (0.007)	–	–	0.009 (0.006)	–	–	–	–	–
-0.010 (0.011)	–	–	–	0.026 (0.028)	–	–	–	–
0.060** (0.025)	–	–	–	–	-0.790*** (0.332)	–	–	–
0.958*** (0.265)	–	–	–	–	–	-0.059*** (0.016)	–	–
0.044*** (0.007)	–	–	–	–	–	–	-0.248*** (0.035)	–
0.007 (0.005)	–	–	–	–	–	–	–	-0.233*** (0.086)

This table presents the results of univariate regressions for an unbalanced panel of 145 US and European banks with a market capitalization larger than USD 2bn between 2006 and 2015. The regressions are performed using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

6.3.2 The Basel ratios' inability to explain *PD* - multivariate regression results

In *Table 6* below, we present the results from the multivariate regressions with each of the Basel ratios as well as the regular equity ratio as independent variables, controlling for size, return on equity and changes in house prices. The results from these regressions are similar to those of the univariate ones in regard to the signs of the coefficients. Three of the Basel ratios are still positively associated with *PD*, however, the liquidity coverage ratio, *LCR*, is now slightly negatively associated with the default risk measure. As in the univariate regressions, none of the Basel ratios show significant impact on *PD*. In contrast to the univariate regression results, the regular equity ratio, *ER*, is now only significant at the 10% level compared to the previous 1% level. With regard to the control variables, both *ROE* and *HOUSE_IND* are still significant and reduce the probability of default, while the size variable only shows a significant association in the regression with the tier 1 capital ratio.

Table 6. Individual Basel ratios as determinants of PD: multivariate panel data regressions

	Expected sign	Actual sign	(1)	(2)	(3)	(4)	(5)
T1CR	(-)	(+)	0.247 (0.125)	–	–	–	–
B_ER	(-)	(+)	–	0.733 (0.347)	–	–	–
LCR	(-)	(-)	–	–	-0.003 (0.011)	–	–
NSFR	(-)	(+)	–	–	–	0.046 (0.024)	–
ER	(-)	(-)	–	–	–	–	-0.360* (0.249)
LN_MV	(-)	(-)	-0.023* (0.018)	-0.021 (0.018)	-0.022 (0.018)	-0.023 (0.018)	-0.021 (0.017)
ROE	(-)	(-)	-0.213*** (0.047)	-0.229*** (0.053)	-0.212*** (0.048)	-0.217*** (0.045)	-0.205*** (0.045)
HOUSE_IND	(-)	(-)	-0.078* (0.050)	-0.084* (0.053)	-0.103** (0.060)	-0.122** (0.063)	-0.120** (0.061)
Year dummies			Yes	Yes	Yes	Yes	Yes
Constant	(-/+)	(+)	0.391* (0.277)	0.341 (0.276)	0.393* (0.280)	0.393* (0.282)	0.410* (0.275)
Dependent variable: PD							
R^2			0.354	0.351	0.343	0.348	0.345
Number of observations			1208	1173	1227	1250	1300
Number of banks			144	144	139	141	145

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn between 2006 and 2015. The regressions are performed using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

In *Panel 1* in *Table 7* below we present the regression results from our main regression model, which includes all Basel ratios and the three additional control variables. Notably, the regular equity ratio, *ER*, is not included in the main regression model as it would create a problem of multicollinearity due to the ratio being highly correlated with the Basel equity ratio, *B_ER*. This correlation is expected since the measures are both equity ratios. A correlation matrix and results of variance inflation factors (VIF) used to assess this problem of multicollinearity is found in *Table A3* in *Appendix*. In addition to the main regression model we also present results from four variations of the model, where the independent variables are combined differently. To allow for a comparison with Blundell-Wignall and Roulet (2012), who use the regular *ER* as the equity ratio, we present the results for our main regression model using the regular *ER* instead of the *B_ER*. The result from this regression is found in *Panel 5*. Furthermore, we find the tier 1 capital ratio to correlate with both the Basel equity ratio and the regular equity ratio and therefore choose to present regression results where those three variables are not included in the same regression. These results are found in *Panel 2*, *3* and *4*.

Table 7. The main regression model, with variations: multivariate panel data regressions

			Main model	Additional models			
	Expected sign	Actual sign	(1)	(2)	(3)	(4)	(5)
T1CR	(-)	(+)	0.045 (0.144)	0.587 (0.194)	0.286 (0.136)	–	–
B_ER	(-)	(+)	0.764 (0.396)	–	–	0.813 (0.353)	–
LCR	(-)	(-/+)	0.005 (0.007)	0.000 (0.008)	-0.002 (0.010)	0.005 (0.007)	0.000 (0.009)
NSFR	(-)	(+)	0.047 (0.036)	0.040 (0.035)	0.039 (0.036)	0.050 (0.033)	0.041 (0.026)
ER	(-)	(-)	–	-1.097*** (0.446)	–	–	-0.523* (0.331)
LN_MV	(-)	(-)	-0.021 (0.018)	-0.016 (0.017)	-0.022 (0.018)	-0.021 (0.018)	-0.018 (0.018)
ROE	(-)	(-)	-0.240*** (0.056)	-0.205*** (0.048)	-0.223*** (0.048)	-0.241*** (0.055)	-0.214*** (0.047)
HOUSE_IND	(-)	(-)	-0.075* (0.050)	-0.077* (0.048)	-0.072** (0.050)	-0.078* (0.050)	-0.122** (0.062)
Year dummies			Yes	Yes	Yes	Yes	Yes
Constant	(-/+)	(+)	0.315 (0.281)	0.304 (0.270)	0.362 (0.284)	0.309 (0.278)	0.360 (0.283)
Dependent variable: PD							
R^2			0.363	0.376	0.361	0.361	0.352
Number of observations			1122	1217	1217	1151	1138
Number of banks			139	139	139	139	139

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn between 2006 and 2015. The regressions are performed using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

Based on the results from our main regression model we do not find any support for our hypotheses. When including the Basel ratios in the same regression we find all four ratios to be positively associated with *PD,* but without any significance. The signs of the coefficients are not in line with what could be expected based on the purpose of the Basel ratios or compared with previous research. However, as previous research has not found significant support for the Basel ratios being able to explain the change in probability of default, we consider our results in line with Blundell-Wignall and Roulet (2012) and Milne (2014). In regard to the control variables, all show the expected signs of the coefficient. Both *ROE* and the house price index are found to be significant.

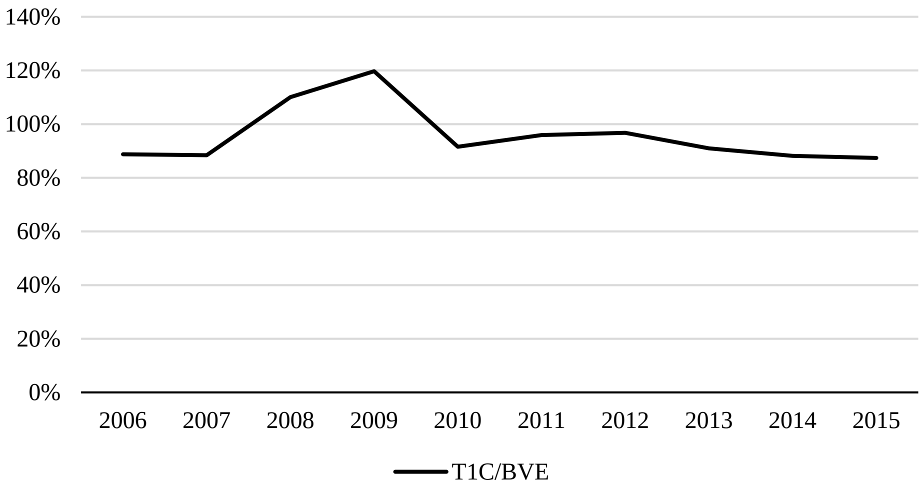
When examining the results across the different regression models, we find the coefficients of the Basel equity ratio and the net stable funding ratio to be consistently positive, while the coefficients of the tier 1 capital ratio and the liquidity coverage ratio vary between positive and negative. However, none of the variations of the main regression model show any significance for the Basel ratios either. In contrast, the regular equity ratio, *ER*, is consistently negative in the two regression models where it is included, significant at the 1% level in the regression presented in *Panel 2* and significant at the 5% level in the regression presented in *Panel 5*. The contrasting results between the Basel equity ratio and the regular *ER* are rather unexpected since the measures are similar to each other. Moreover, the negative association between *ER* and *PD* is in line with the results of Blundell-Wignall and Roulet (2012).

The predictive power of the model is represented by R^2, which expresses the proportion of the change in the dependent variable that can be explained by the independent variables in the regression. Examining the R^2 in the regression models, we see levels ranging from 0.352 to 0.376. It might appear low to only be able to explain 35.2-37.6% of the changes in a variable, however, given the type of dependent variable included in the model, we deem the results to be acceptable. The probability of default is a complex measure, and it is not realistic to expect to include all variables that are able to explain changes in *PD*.

6.4 Building on the regression results: additional analysis of T1C and BV_E

As previously discussed, the Basel equity ratio and the regular equity ratio are highly correlated, which is expected since both ratios are variations of equity ratios. Therefore, we would believe the two ratios to have similar effects on *PD*. However, the regression results indicate that an increase in the Basel equity ratio would increase the default risk, while an increase in the regular equity ratio would have the opposite effect. This seems contradictory, as tier 1 capital (*T1C*) is part of what makes up total book value of equity (*BV_E*) and one would therefore also expect an increase in *T1C* to correspond to a decrease in *PD*. The positive association between the Basel equity ratio and *PD* is insignificant, but it is still of interest to investigate the difference in the coefficients. In order to understand the contradiction, we look at the ratio between actual levels of tier 1 capital over the sample period and actual levels of book value of equity. The result is illustrated in *Figure 3* below. As can be seen, the relation between *T1C* and *BV_E* was affected by the financial crisis in 2008 and 2009, resulting in a ratio between *T1C* and *BV_E* that is higher than 100%.

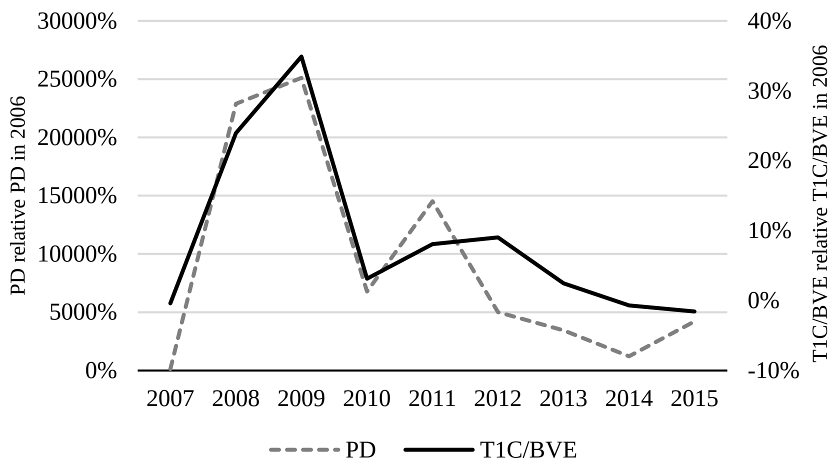
Figure 3. Development of T1C/BV_E 2006-2015



This table shows the development of the relation between tier 1 capital (*T1C*) and book value of equity (*BV_E*) over the years 2006-2015.

Moreover, if we compare the development of the ratio illustrated in *Figure 3* on the previous page with the development of the probability of default, an interesting pattern can be seen where the development of *PD* and $T1C/BV_E$ follow a rather similar trend line over the years. Year 2006 is used as a basis for the calculation of the relative increase for each year. For example, in year 2009 the average *PD* for our sample is 250 times higher than in 2006, and the average $T1C/BV_E$ is 0.35 times higher than in 2006. We illustrate this trend line in *Figure 4* below.

Figure 4. Trend lines for change in PD and in $T1C/BV_E$



This table shows the changes in probability of default (*PD*) and the relation between tier 1 capital (*T1C*) and book value of equity (BV_E) over the years 2006-2015. Year 2006 is used as basis for calculation of the relative size of *PD* and $T1C/BV_E$ each year. The left axis represents the relative increase in *PD*, while the right axis shows the relative increase in $T1C/BV_E$.

6.5 Robustness tests

From the results of the main regression model we conclude that all four Basel ratios are positively associated with *PD*. However, none of these variables have a significant association with the default risk measure. In order to test the robustness of these results we perform the main regression model and its variations with a division between three different categories. These categories are region, time period in terms of before and after the start of the Basel III implementation, and time period in terms of the time period included in previous studies.

6.5.1 Regional

In order to capture potential differences between European and US banks we perform a study of the association between the probability of default, *PD*, and the Basel ratios split per region. *Panel 1* represents our main regression model, including all four Basel ratios. *Panel 2* presents the results from the main regression model excluding the Basel equity ratio, *B_ER*. *Panel 3* presents the results from the main regression model excluding the tier 1 capital ratio, *T1CR*. Each regression is performed for Europe and the US separately and the results are presented in *Table 8* below (for additional regression results split on region, see *Table A4* in Appendix).

Table 8. Robustness test: regional split

	Expected sign	Actual sign	Europe (1)	Europe (2)	Europe (3)	Expected sign	Actual sign	US (1)	US (2)	US (3)
T1CR	(-)	(-/+)	-0.104 (0.131)	0.032 (0.117)	–	(-)	(+)	0.603 (0.491)	0.240 (0.241)	–
B_ER	(-)	(+)	0.761 (0.324)	–	0.639 (0.280)	(-)	(-/+)	-0.650 (0.771)	–	0.167 (0.378)
LCR	(-)	(+)	0.009 (0.007)	0.000 (0.006)	0.009 (0.007)	(-)	(-)	-0.079 (0.086)	-0.039 (0.074)	-0.020 (0.072)
NSFR	(-)	(+)	0.043 (0.023)	0.035 (0.023)	0.043 (0.022)	(-)	(-)	-0.023 (0.084)	-0.029 (0.083)	-0.026 (0.084)
ER			–	–	–			–	–	–
LN_MV	(-)	(-)	-0.014*** (0.007)	-0.014*** (0.007)	-0.014*** (0.006)	(-)	(-)	-0.068*** (0.019)	-0.067*** (0.019)	-0.069*** (0.019)
ROE	(-)	(-)	-0.184*** (0.019)	-0.179*** (0.018)	-0.184*** (0.019)	(-)	(-)	-0.382*** (0.076)	-0.385*** (0.076)	-0.387*** (0.076)
HOUSE_IND	(-)	(-)	-0.019 (0.038)	-0.022 (0.040)	-0.019 (0.038)	(-)	(-)	-0.331 (0.569)	-0.344 (0.564)	-0.320 (0.569)
Year dummies			Yes	Yes	Yes			Yes	Yes	Yes
Constant	(-/+)	(+)	0.210*** (0.106)	0.258*** (0.108)	0.215*** (0.104)	(-/+)	(+)	1.152*** (0.301)	1.117*** (0.298)	1.153*** (0.300)
Dependent variable: PD										
R^2			0.269	0.279	0.268			0.590	0.588	0.588
Number of observations			696	718	707			430	433	431
Number of banks			92	92	92			47	47	47

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn between 2006 and 2015. The regressions are performed and presented for Europe and the US separately, using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

In contrast to the original results for the main regression model, the tier 1 capital ratio has a negative, but insignificant, association with probability of default when examining the European sample. However, when observing the results from the US sample, we find that the coefficients of the Basel ratios are opposite those of the European sample. *T1CR* is positively associated with PD, while *B_ER*, *LCR* and *NSFR* all are negatively associated with *PD*. Although, none of the ratios are significant, and therefore we draw the conclusion that none of the Basel ratios appear to be useful for preventing increases in probability of default when examining the different regions separately. In regards to the variations of the main regression model, they do not yield any significant results for the Basel ratios either.

6.5.2 Before and after Basel III implementation

As previously mentioned, the calculation of tier 1 capital and risk-weighted assets was amended through the Basel III implementation in 2013, and we therefore choose to investigate whether the results for the main regression model, and two of its variations, are different if we divide the observations into before and after the Basel III implementation. For the purpose of this analysis, we focus specifically on the tier 1 capital ratio and the Basel equity ratio. The results are found in *Table 9* below and additional regression results, split on time period, can be found in *Table A5* in Appendix.

Table 9. Robustness test: Before and after the implementation of Basel III

	Expected sign	Actual sign	Before Basel III			Expected sign	Actual sign	After Basel III		
			(1)	(2)	(3)			(1)	(2)	(3)
T1CR	(-)	(-/+)	-0.053 (0.241)	0.366 (0.175)	–	(-)	(+)	0.045 0.358	0.046 (0.233)	–
B_ER	(-)	(+)	1.199 (0.453)	–	1.126 (0.327)	(-)	(+)	0.026 0.671	–	0.081 (0.448)
LCR	(-)	(+)	0.001 (0.012)	0.003 (0.012)	0.001 (0.012)	(-)	(+)	0.138 (0.053)	0.074 (0.042)	0.139 (0.052)
NSFR	(-)	(-/+)	0.003 (0.052)	-0.002 (0.052)	0.002 (0.051)	(-)	(+)	0.078 (0.036)	0.081 (0.036)	0.078 (0.036)
ER			–	–	–			–	–	–
LN_MV	(-)	(-)	-0.011 (0.010)	-0.010 (0.010)	-0.011 (0.010)	(-)	(-)	-0.019 (0.020)	-0.005 (0.020)	-0.019 (0.020)
ROE	(-)	(-)	-0.317*** (0.036)	-0.327*** (0.033)	-0.317*** (0.036)	(-)	(-)	-0.047** (0.026)	-0.018 (0.025)	-0.047* (0.026)
HOUSE_IND	(-)	(-)	-0.072 (0.092)	-0.034 (0.090)	-0.066 (0.090)	(-)	(-)	-0.022 (0.045)	-0.022 (0.045)	-0.021 (0.045)
Year dummies			Yes	Yes	Yes			Yes	Yes	Yes
Constant	(-/+)	(+)	0.161 (0.158)	0.173 (0.156)	0.156 (0.157)	(-/+)	(+)	0.212 (0.331)	0.015 (0.321)	0.212 (0.329)
Dependent variable: PD										
R^2			0.387	0.399	0.384			0.096	0.063	0.096
Number of observations			793	808	804			333	343	334
Number of banks			131	131	131			122	122	122

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn. The regressions are performed for the two time periods 2006-2012 and 2013-2015 separately, using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

In contrast to the regression results over the complete sample period, we would expect *T1CR* to be a better predictor of *PD* during 2013-2015, as amendments were made to the standards aiming to improve the calculation of tier 1 capital and RWA (BCBS, 2011). However, the results show that *T1CR* has the expected sign, but is insignificant in our main regression model for the years after 2013. No significant association between *T1CR* and *PD* are found for the years before 2013 either. The same result holds for the Basel equity ratio, showing a positive but insignificant association with *PD*, similar to the result from the main regression model.

6.5.3 Sample period ending 2011

In order to further compare the results of our main regression model with the findings of Blundell-Wignall and Roulet (2012), we choose to present our main regression model results by using a sample period ranging between 2006 and 2011, which was the last year included in the study of Blundell-Wignall and Roulet. The results are presented in *Table 10* below.

Table 10. Robustness test: time period 2006-2011

	Expected sign	Actual sign	Main model (1)	(2)	(3)
T1CR	(-)	(-/+)	-0.099 (0.290)	0.435 (0.207)	–
B_ER	(-)	(+)	1.465 (0.538)	–	1.324 (0.381)
LCR	(-)	(+)	0.003 (0.014)	0.004 (0.014)	0.003 (0.013)
NSFR	(-)	(-/+)	0.003 (0.062)	-0.003 (0.061)	0.001 (0.060)
ER			–	–	–
LN_MV	(-)	(-)	-0.008 (0.012)	-0.007 (0.012)	-0.008 (0.012)
ROE	(-)	(-)	-0.348*** (0.048)	-0.354*** (0.041)	-0.349*** (0.048)
HOUSE_IND	(-)	(+)	0.039 (0.115)	0.069 (0.113)	0.048 (0.112)
Year dummies			Yes	Yes	Yes
Constant	(-/+)	(+)	0.101 (0.185)	0.119 (0.183)	0.098 (0.184)
Dependent variable: PD					
R^2			0.461	0.374	0.387
Number of observations			694	690	682
Number of banks			130	130	130

This table reports table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn between 2006 and 2011. The regressions are performed and presented for Europe and the US separately, using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

In contrast to the results using the time period 2006-2015, we now find that the associations between tier 1 capital ratio and the probability of default is more in line with the results of Blundell-Wignall and Roulet since the coefficient has a negative sign. Also, similar to the results of Blundell-Wignall and Roulet there are still no significant results, indicating that the tier 1 capital ratio is not effective in preventing increases in probability of default.

7. Discussion and problematization

In this section we discuss our results further and examine how they relate to findings in previous research. We acknowledge that our findings are dependent on a number of assumptions that are likely to affect our results and therefore we also discuss some of the issues that might occur due to these assumptions.

7.1 Discussion

In our regression results we find all Basel ratios to show positive relations with *PD*, indicating that increases in these four ratios respectively increase the default risk. These results are opposite to what is expected and contradict the purpose of the Basel regulatory tools. However, since the measures are not significant we cannot draw any conclusions regarding the direction of the association between the measures and *PD*. Furthermore, since no significance for an association between the Basel ratios and *PD* can be found we interpret this as an indication that the measures might not be relevant when aiming to decrease probability of bank default. These insignificant results are also in line with the findings of previous research. For example, Blundell-Wignall and Roulet (2012) and Milne (2014) do not find the *T1CR* to have any significant association with *PD*. As for the *LCR* and the *NSFR*, Hong et al. (2014) do not find any significant associations between the ratios and default risk either. Hong et al., in line with the results of our main regression model, also find a positive association between *LCR* and probability of default and explaining this by the fact that banks anticipating financial distress increase their liquidity buffers. However, as this result is not significant they cannot with statistical certainty claim that the association between *PD* and *LCR* is true.

An interesting finding is that we obtain opposite signs for the coefficients of the Basel equity ratio, *B_ER*, and the regular equity ratio, *ER*, in both our main regression model and the variations of the main regression models in *Table 7* in *Section 6.3.2*. Both measures represent capital buffers that aid in preventing defaults due to unexpected losses during times of financial distress. However, *ER* is the only variable that shows a significant negative association with probability of default, which is the expected result for the Basel equity ratio as well. Even though *B_ER* is not significant it is of interest to aim to find an explanation to these differences. We do this by examining the construction of the different measures. In our study, the measures share a common denominator, total assets, but the numerator is what makes the measures differ, i.e. tier 1 capital and book value of equity for *B_ER* and *ER* respectively. The comparison show that the tier 1 capital is smaller than the book value of equity most of the time, which is expected since tier 1 capital essentially is book value of equity, but with exclusions of certain items (such as a proportion of innovative financial instruments). However, during the peak of the financial crisis, more specifically year 2008 and 2009, we find that average tier 1 capital in fact exceeds book value of equity. We also examine the change in $T1C/BV_E$ and *PD* relative the levels of 2006 in *Table 8* in *Section 6.3.2*. Interestingly, we find that the two measures follow an evidently similar trend, meaning that a relative increase in *T1C* to BV_E, i.e. an increase in the Basel equity ratio relative the regular equity ratio, coincides with an increase in the probability of default. Thus, this relation could aid in explaining the opposite coefficient signs of *B_ER* and *ER*. In regards to the reasons behind the relative increase of *T1C* to BV_E during the financial crisis, we acknowledge the need to analyze the specific items that differentiate *T1C* from BV_E. However, we deem this detailed analysis to be outside the scope of this paper.

Notably, the results from our robustness tests show that the Basel ratios are insignificant also when splitting the sample based on region and time period. Interestingly, our third robustness test, i.e. when we only include the years up until year 2011, which is the last year included in both Blundell-Wignall and Roulet's (2012) study and Milne's (2014) study, we receive the expected negative association between *T1CR* and *PD*. However, in line with the previous research we still do not receive any significant results for the association between tier 1 capital ratio and the probability of default.

7.2 Problematization

Firstly, two of the Basel ratios assessed in this study have not been implemented yet, which means that banks have not started to report any values for these two ratios. To capture the same aspects that the Basel ratios aim for, we have used proxies for these ratios. However, the proxies are only proxies, meaning that if we would have been able to study reported values of *LCR* and *NSFR* directly, following the definitions in the Basel framework, we would most likely have received different associations with the probability of default, which might have been correctly signed and significant. Nevertheless, we think that our proxies should reflect the same aspects as the actual ratios and the insignificant results are therefore of interest. Secondly we did not have access to the information necessary to adjust the *B_ER* for off-balance sheet items, which should be done according to the Basel definition, but we do not believe that this adjustment would change the result.

Similar to Blundell-Wignall and Roulet (2012), we find a significant negative association between the regular *ER* and *PD*, meaning that an increase in the regular equity ratio is associated with a decrease in the probability of default. Even though these findings are in line with our expectations, we believe it to be of importance to question them. Since the probability of default is constructed using the market value of equity and the market value of assets as inputs, we acknowledge that this could create an inherent association between the calculated *PD* and the regular equity ratio since book value of equity is closely related to the market value of equity and the book value of assets is closely related to the market value of assets. However, since *ER* is not always significant at the 5% level or below in our regressions we do not consider this to be a problem.

Another issue is the availability of data for banks in Datastream, which affects our choices of control variables in the regression model. Previous research within this field controls for variables such as wholesale funding, trading assets and gross market value of derivatives exposure (Blundell-Wignall and Roulet, 2012; Milne, 2014), which could have been useful for us as well but those data points are only available for a small number of our sample banks and are therefore not included in the regression model. Controlling for other variables that might affect the probability of default could have resulted in other associations between the Basel ratios and the default risk measure.

8. Conclusion

After the financial crisis starting in 2008, the Basel Committee on Banking Supervision revised the Basel framework with the aim of preventing future bank failures. However, the Basel framework has been criticized for focusing on overly complex measures. Therefore, this study assesses the relevance of four key Basel capital and liquidity ratios; the tier 1 capital ratio, the leverage ratio (in this study renamed the Basel equity ratio since the ratio in fact measures equity), the liquidity coverage ratio and the net stable funding ratio, as predictors of default risk. Our sample includes 145 European and US banks over the time period 2006-2015.

From the focus of the Basel Accords it is apparent that prevention of future bank defaults is one of the main objectives and researchers have therefore started to investigate the usefulness of the Basel ratios in decreasing the probability of default. To perform this sort of evaluation of the Basel ratios we find it important to use a measure of default risk that reflects reality as accurately as possible. As starting point for this paper we therefore use a recent study by Blundell-Wignall and Roulet (2012) that investigates the effectiveness of the tier 1 capital ratio as a predictor of default risk. From their study, we identify four adjustments that can be made to their default risk measure distance-to-default, used for evaluating the relevance of the tier 1 capital ratio. After performing the four adjustments we obtain a market-based default risk measure that considers default risk over time and cash outflows affecting the value of the firm's assets, i.e. dividends and coupon payments. Expected asset returns are also included in the calculation of the measure to reflect real world probabilities rather than risk-neutral ones. Lastly, we transform the distance-to-default measure into an actual probability measure as we consider it more intuitive to analyze.

After arriving at a default risk measure that we believe better reflects reality, we regress the obtained probability of default against the four Basel ratios and control for return on equity, size and house price changes. We find no support for our first hypothesis as neither the tier 1 capital ratio, the Basel equity ratio, the liquidity coverage ratio nor the net stable funding ratio are found to be negatively associated with the risk measure, i.e. higher Basel III ratios are not found to be related to lower probability of defaults. This suggests that the Basel ratios might not be relevant in preventing increases in default risk. Our findings are in line with previous research, as none of the studies by Blundell-Wignall and Roulet (2012), Milne (2014) and Flannery and Giacomini (2015) are able to find a significant association between the tier 1 capital ratio and bank default risk either. Neither Hong et al. (2014) nor Hartlage (2012) find any strong support for LCR and NSFR being able to predict changes in probability of default. Since neither the tier 1 capital ratio nor the Basel equity ratio are found to have any significant association with the probability of default we fail to find any proof for our second hypothesis that the Basel equity ratio has a more significant association with the probability of default than the tier 1 capital ratio. In contrast to the Basel ratios, we find that the regular equity ratio has a significantly negative association with the risk measure in our study, which is in line with the results of Blundell-Wignall and Roulet. However, the difference in results between the Basel equity ratio and the regular equity ratio is surprising due to the similarity of the two measures. A possible explanation for these diverging results are that the numerators of the two equity ratios move in opposite directions during the financial crisis.

Finally, even though our findings regarding the relevance of the Basel III ratios do not differ from previous research covered in this study, we believe that this study and the adjustments made to the risk measure reinforces the results from the limited research available within this research field.

For future research we suggest to investigate the differences between the calculations of risk-weighted assets according to the standardized versus the advanced approaches further, since the internal models are likely to affect the tier 1 capital ratio. Furthermore, we recognize the need to investigate the question of the relevance of the Basel III ratios in preventing bank failures as the implementation progress, as well as when the implementation has been finalized. Not only will there be more years of observations for the updated tier 1 capital ratio and the Basel equity ratio, but there will be reported levels of the liquidity ratios; LCR and NSFR. As explained previously, the liquidity measures in our study are proxies, and having access to the reported number of LCR and NSFR might change the results from the regression analysis.

9. References

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Appendix

Table A1: List of banks

Name	Country	Market Cap 06	Avg 06-15	Name	Country	Market Cap 06	Avg 06-15
HSBC	UK	211	178	Alpha Bank	Greece	12	7
JP Morgan & Chase	US	168	175	German Landesbanken	Germany	10	7
Wells Fargo	US	120	175	Comercia	US	9	7
Bank of America	US	240	147	First Republic Bank	US	0	6
Citigroup	US	274	136	Bank of Piraeus	Greece	9	6
Banco Santander	Spain	117	98	New York Community Bank	US	5	6
Wachovia	US	90	81	Banco Espirito	Portugal	9	6
BNP Paribas	France	101	77	Hudson City Bank	US	8	6
Goldman Sachs	US	85	73	Banco Comercial Portugues	Portugal	13	6
UBS	Switzerland	128	70	Huntington	US	6	6
Lloyds Banking	UK	63	64	Banco Popolare	Italy	11	6
BBV Argentaria	Spain	85	61	Finansbank	Turkey	5	5
US Bankcorp	US	64	60	Turkiye Vakiflar Bankasi	Turkey	6	5
Barclays	UK	93	55	Islandsbanki	Iceland	4	5
Morgan Stanley	US	85	51	Peoples United	US	6	5
HBOS	UK	83	50	Bankinter	Spain	6	5
Credit Suisse	Switzerland	85	50	Glitnir Banki	Iceland	5	5
ING Group	Netherlands	98	50	Zions Bancorporation	US	9	5
Unicredit	Italy	91	49	Finecobank	Italy	0	4
RBS	UK	123	48	mBank	Poland	3	4
Standard Chartered	UK	40	46	Banque Canton	Switzerland	4	4
Intesa Sanpaolo	Italy	46	46	Synovus Financial	US	10	4
Deutsche Bank	Germany	70	45	TFS Financial	US	0	4
Societe Generale	France	78	43	ING Bank Slaski	Poland	3	4
Nordea	Sweden	40	40	BOK Financial Corporation	US	4	4
Lehman Brothers	US	41	38	BPER Banca	Italy	6	4
Credit Agricole	France	63	35	Handlowy	Poland	4	4
PNC Financial Services	US	22	32	Commerce Bank	US	3	4
Dexia	Belgium	31	30	Cullen/Frost Bankers	US	3	4
Allied Irish	Ireland	26	27	IKB Deutsche Industriebank	Germany	3	3
Washington Mutual	US	43	27	DenizBank	Turkey	3	3
KBC Group	Belgium	45	22	Bank of Cyprus	Cyprus	8	3
BB&T	US	24	21	Banca Carige	Italy	6	3
Handelsbanken	Sweden	19	21	Banca Popolare di Milano	Italy	7	3
Danske Bank	Denmark	31	21	Jyske Bank	Denmark	4	3
Caixa	Spain	0	20	Signature Bank	US	1	3
DNB	Norway	19	20	East West	US	2	3
SEB	Sweden	21	19	City National Bank	US	4	3
Suntrust Banks	US	30	18	First Horizon	US	5	3
Swedbank	Sweden	19	18	SVB Financial Group	US	2	3
Natixis	France	34	17	Zagrebacka Banka	Croatia	4	3
AK Bank	Turkey	13	16	Associated Banc-Corp	US	5	3
Commerzbank	Germany	25	15	Banca Popolare di Sondrio	Italy	4	3
PKO Bank	Poland	16	15	First Niagara	US	2	3
Garanti Bank	Turkey	7	15	Banco BPI	Portugal	6	3
Bear Stearns	US	19	15	Luzerner Kantonalbank	Switzerland	2	3
Turkiye Halk Bankasi	Spain	0	15	EFG International	Switzerland	6	3
Erste Group	Austria	24	14	Credito Emiliano	Italy	4	2
Bank Polska Kasa Opieki	Poland	13	14	CapitalSource	US	5	2
National Bank of Greece	Greece	22	14	Privredna Banka	Croatia	4	2
Fifth Third Bank	US	23	14	Permanent TSB	Ireland	7	2
Anglo Irish Bank	Ireland	15	14	Bank of Hawaii	US	3	2
M&T Bank	US	14	12	Prosperity Bank	US	1	2

Table A1: List of banks (continued)

Name	Country	Market Cap 06	Avg 06-15	Name	Country	Market Cap 06	Avg 06-15
Regions Financial Corp.	US	27	12	Investors Bank	US	2	2
Turkiye Is Bankasi	Turkey	13	12	Valley National Bank	US	3	2
Banco Popular	Spain	22	11	TCF	US	4	2
Raiffeisen Bank	Austria	22	10	St.Galler Kantonalbank	Switzerland	2	2
Mediobanca Bank	Italy	19	10	Vontobel Holding	Switzerland	3	2
Kaupthing Bank	Iceland	9	10	Virgin Money	UK	0	2
Bank of Ireland	Ireland	23	9	FirstMerit Bank	US	2	2
Julius Bar Gruppe	Switzerland	0	9	Capitol Federal	US	3	2
Deutsche Postbank	Germany	14	9	Valiant	Switzerland	2	2
Keycorp	US	15	9	Bank Millennium	Poland	2	2
Banco de Sabadell	Spain	14	9	Fulton Financial	US	3	2
Halk Bankasi	Turkey	0	9	Webster Financial	US	3	2
Yapi Kredi	Turkey	5	9	Berner Kantonalbank	Switzerland	2	2
UBI Banca	Italy	9	8	Sydbank	Denmark	3	2
CIC	France	13	8	Hancock Bank	US	2	2
Sallie Mae	US	20	8	Washington Federal	US	2	2
Komercni Banka	Czech Republic	6	8	BancorpSouth	US	2	2
Banca Monte dei Paschi	Italy	16	7	LLB	Lithuania	3	2
OTP	Hungary	13	7	Astoria	US	3	2
Eurobank Ergasias	Greece	14	7				

This table presents the 145 banks and their respective market capitalization year 2006 as well as the average market capitalization during the sample period 2006-2015 (shorter for banks that failed or were listed during the sample period). All values are expressed in USD bn.

Table A2. Hausman test

	Fixed effects	Random effects	Difference
T1CR	-0.338	-0.313	-0.025
B_ER	0.955	0.829	0.126
LCR	0.008	0.002	0.006
NSFR	0.058	-0.002	0.060
LN_MV	-0.044	0.006	-0.051
ROE	-0.212	-0.274	0.062
HOUSE_IND	-0.271	-0.313	0.042
Hausman test:			
Statistic	103.35		
p-value	0.0000		

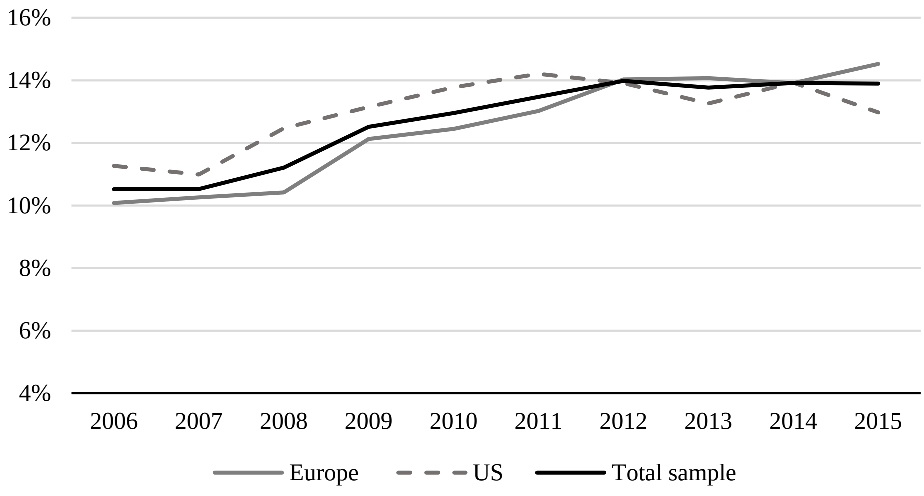
This table shows the Hausman test, which assesses if a fixed effects or random effects regression is preferred. Since the *p*-value is below 0.05, a fixed effects regression is preferred.

Table A3. Descriptive statistics of the probability of default 2006-2015

	Total sample										
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	All years
Number of obs.	137	139	127	129	130	129	125	131	131	126	1304
Mean	0.06	0.13	13.71	15.04	4.11	8.73	3.05	2.11	0.79	2.57	4.95
Median	0.00	0.01	6.99	7.08	0.28	1.68	0.41	0.01	0.01	0.06	0.13
Max	1.45	2.19	75.79	89.54	74.21	72.87	48.24	66.69	21.09	51.38	89.54
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev	0.22	0.34	17.35	19.00	10.44	15.98	7.37	8.69	2.80	9.13	12.23
	Europe										
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	All years
Number of obs.	87	88	80	82	83	81	77	83	84	81	826
Mean	0.09	0.12	6.79	6.77	2.59	4.66	2.74	3.23	1.13	3.70	3.13
Median	0.00	0.01	3.44	3.44	0.12	0.93	0.41	0.07	0.01	0.04	0.12
Max	1.45	1.40	65.04	42.95	74.21	69.15	48.24	66.69	21.09	51.38	74.21
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev	0.26	0.24	10.07	9.16	9.58	11.78	7.45	10.78	3.38	11.23	8.71
	US										
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	All years
Number of obs.	50	51	47	47	47	48	48	48	47	45	478
Mean	0.00	0.16	25.50	29.46	6.78	15.60	3.55	0.18	0.17	0.53	8.10
Median	0.00	0.01	19.60	23.06	1.77	6.81	0.45	0.01	0.00	0.13	0.14
Max	0.00	2.19	75.79	89.54	58.23	72.87	37.65	4.51	6.42	5.07	89.54
Min	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev	0.00	0.47	20.62	22.86	11.44	19.57	7.30	0.69	0.93	0.99	16.17

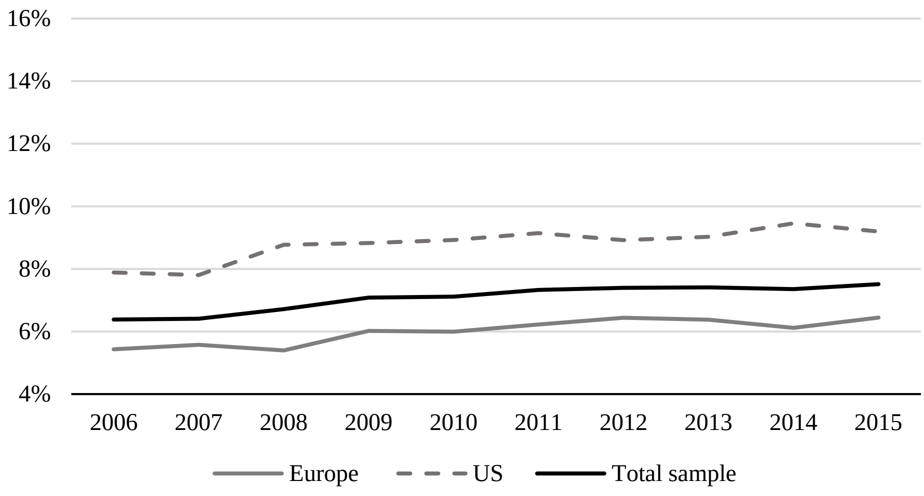
This table shows descriptive statistics for the probability of default for the total sample, as well as for Europe and the US respectively. All values are presented in percentages, apart from the number of observations.

Figure A1. Average T1CR 2006-2015



This table illustrates the average tier 1 capital ratio (T1CR) over the years 2006-2015 for the whole sample of 145 banks and with regional splits for Europe and US.

Figure A2. Average B_ER 2006-2015



This table illustrates the average Basel equity ratio (B_ER) over the years 2006-2015 for the whole sample of 145 banks and with regional splits for Europe and US.

Table A3. Correlation matrix and variance inflation factors

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	VIF (a)	VIF (b)
(1)	T1CR	1.000								1.400	1.390
(2)	B_ER	0.456	1.000							**3.150**	1.640
(3)	LCR	0.004	-0.361	1.000						1.480	1.450
(4)	NSFR	0.118	-0.081	0.358	1.000					1.230	1.200
(5)	ER	0.416	0.798	-0.305	-0.005	1.000				**2.820**	–
(6)	LN_MV	-0.172	-0.333	0.281	0.158	-0.247	1.000			1.250	1.25
(7)	ROE	0.032	0.071	-0.061	0.041	0.109	0.192	1.000		1.100	1.090
(8)	HOUSE_IND	0.056	-0.016	0.012	0.022	-0.016	0.151	0.203	1.000	1.070	1.070

This table presents the correlation between all independent variables, as well as the variance inflation factors (VIF). VIF(a) presents the results for all independent variables, while VIF(b) presents the results for the independent variables in the main model, i.e. excluding ER. A VIF of above 2.0 is considered to reflect a problem of multicollinearity.

Table A4. Comparing multivariate regression results between US and Europe

	Europe					US				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T1CR	0.005 (0.115)	–	–	–	–	0.074 (0.223)	–	–	–	–
B_ER	–	0.555 (0.274)	–	–	–	–	0.088 (0.377)	–	–	–
LCR	–	–	-0.001 (0.006)	–	–	–	–	-0.031 (0.056)	–	–
NSFR	–	–	–	0.026 (0.020)	–	–	–	–	0.032 (0.052)	–
ER	–	–	–	–	0.120 (0.156)	–	–	–	–	-0.846*** (0.278)
LN_MV	-0.017*** (0.007)	-0.015*** (0.006)	-0.015*** (0.006)	-0.016*** (0.006)	-0.020*** (0.006)	-0.065*** (0.019)	-0.065*** (0.019)	-0.070*** (0.019)	-0.067*** (0.018)	-0.065*** (0.018)
ROE	-0.171*** (0.017)	-0.175*** (0.018)	-0.171*** (0.017)	-0.174*** (0.017)	-0.172*** (0.017)	-0.393*** (0.071)	-0.410*** (0.074)	-0.395*** (0.074)	-0.351*** (0.069)	-0.339*** (0.068)
HOUSE_IND	-0.024 (0.040)	-0.015 (0.037)	-0.031 (0.038)	-0.041 (0.038)	-0.037 (0.038)	-0.402 (0.557)	-0.331 (0.570)	-0.254 (0.554)	-0.280 (0.564)	-0.192 (0.550)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.314*** (0.108)	0.253** (0.103)	0.288*** (0.103)	0.295*** (0.102)	0.349*** (0.103)	1.084*** (0.293)	1.091*** (0.302)	1.167*** (0.290)	1.097*** (0.284)	1.164*** (0.281)
Dependent variable: PD										
R^2	0.277	0.259	0.269	0.273	0.273	0.575	0.575	0.589	0.578	0.580
Number of observations	750	724	791	798	824	458	449	436	452	476
Number of banks	93	93	92	93	93	51	51	47	48	52

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn between 2006 and 2015. The regressions are performed for Europe and the US separately, using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.

Table A5. Comparing multivariate regression results before and after Basel III implementation

	Before Basel III		After Basel III	
	T1CR (1)	B_ER (2)	T1CR (3)	B_ER (4)
T1CR	0.286 (0.168)	–	0.037 (0.228)	–
B_ER	–	1.061 (0.326)	–	-0.084 (0.450)
LCR	–	–	–	–
NSFR	–	–	–	–
ER	–	–	–	–
LN_MV	-0.012 (0.010)	-0.012 (0.010)	-0.013 (0.018)	-0.023 (0.020)
ROE	-0.310*** (0.031)	-0.296*** (0.034)	-0.028 (0.024)	-0.052** (0.026)
HOUSE_IND	-0.037 (0.089)	-0.068 (0.089)	-0.023 (0.045)	-0.020 (0.045)
Year dummies (a)	Yes	Yes	Yes	Yes
Constant	0.220 (0.154)	0.172 (0.156)	0.225 (0.296)	0.396 (0.332)
Dependent variable: PD				
R^2	0.388	0.372	0.027	0.042
Number of observations	848	824	360	349
Number of banks	140	135	131	128

This table reports the results of multivariate regressions for an unbalanced panel of US and European banks with a market capitalization larger than USD 2bn. The regressions are performed for the two time periods 2006-2012 and 2013-2015 separately, using cross-section and time fixed effects. *, **, *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors are presented within the parentheses, below the coefficients.