Comparability of Basel risk weights in the EU banking sector

Sophia Döme,
Stefan Kerbl[1]

Refereed by:
Markus Behn,
European Central Bank

Our aim is to quantify the variability across EU countries evident in the risk weights (RW) applied by banks to their exposures. To this end, we use a publicly available panel dataset which provides granular portfolio-by-portfolio data for major EU banks and covers six periods between 2013 and 2016. In line with the Basel regulatory capital framework, RW should adequately mirror the risk of the obligations. One meaningful indicator of the underlying risk is the share of nonperforming loans (NPLs) in a given portfolio. We show that a good portion of RW variability can be explained by portfolio- and destination-specific risk indicators such as macroeconomic indicators and NPL ratios. In our analysis, we find that it is not statistically significant that large banks are better able to push down RW (after controlling for underlying credit risks). It is of marginal statistical significance that banks with low common equity tier 1 (CET1) ratios employ RW that are lower than would be expected from the underlying credit risk. We observe, however, statistically significant and economically important differences with regard to the country where a bank is headquartered. The paper sets forth evidence that implementation standards differ from jurisdiction to jurisdiction, thus motivating initiatives by the EBA and the ECB to strengthen harmonization.

JEL classification: G21, G28, E61, G38
Keywords: bank capital, regulation, risk weights, Basel regulatory capital frameworks

The prime rationale for Basel II was to strengthen the regulatory capital framework by ensuring that banks' capital allocation is more risk sensitive. Basel II hence permitted banks to use internal risk models to quantify their capital requirements for credit risk (the so-called internal ratings-based (IRB) approach) instead of the risk weight table under Basel I. Banks had already begun to employ such risk models in their own management and were now allowed, upon supervisory approval, to use them to calculate their capital requirements. As an alternative, Basel II allowed banks to employ a simpler standardized approach for calculating the risk inherent in their exposures.

The objective of model-based capital requirements was to obtain higher risk sensitivity and thus increase the efficiency of credit allocation. However, this objective had to be weighed against banks' incentives to use "artificially low" internal estimates. Naturally, supervisors have to prevent the latter from happening. Another concern was whether differences in banks' and supervisory standards regarding the implementation of models would make the outcomes comparable across jurisdictions.

Several studies examining whether supervisors were able to prevent banks from embellishing capital ratios found concerning discrepancies in risk weights across banks and jurisdictions.[2] Therefore, international bodies like the Basel Committee on Banking Supervision (BCBS) and the European Banking Authority (EBA) responded by strengthening their focus on the topic. A number of studies also showed that many banks that rely on internal models for calculating regulatory capital overstate their

[1] *Oesterreichische Nationalbank, Financial Stability and Macroprudential Supervision Division, zsofia.doeme@oenb.at and stefan.kerbl@oenb.at. The views expressed in this paper are exclusively those of the authors and do not necessarily reflect those of the OeNB or the Eurosystem. The authors would like to thank Markus Behn (ECB) for helpful comments and valuable suggestions.*

[2] *For example, Behn et al. (2016) provide an overview of the literature on risk weight heterogeneity, and the BCBS (2013) summarizes the BIS RCAP analyses.*

capital ratios by reducing the risk weights (RW) (Vallascas and Hagendorff, 2013; Mariathasan and Merrouche, 2014; Behn et al., 2016; Bruno et al., 2016). Such practices would have grave consequences for banking regulation, which largely relies on capital requirements. For this reason, some researchers (e.g. Haldane, 2012) argue that banking regulation should become less complex, a view that has attracted growing support recently (BCBS, 2016b). With the transition to IFRS 9, internal credit risk models will also be used to determine credit risk provisions. Against this backdrop, the comparability of banks' internal model outcomes will be even more relevant.

We set out to investigate the main determinants of RW heterogeneity, focusing on the question to which extent cross-country differences in risk weights[3] can be explained by bank-specific factors. According to the Basel regulatory framework, what we would like to dub "*intended* risk weight heterogeneity" is due to differences in actual underlying risks. By contrast, "*unintended* risk weight heterogeneity" arises when banks' and supervisory standards are implemented differently from jurisdiction to jurisdiction and also when artificially low internal estimates come into play.

We use an extensive, granular dataset on major European banks from the EBA transparency exercises. This dataset is very rich in dimensionality (banks, asset classes, IRB vs. standardized approach, destination country of exposures and time breakdown). This allows us to study risk weights on a very granular level (e.g. the RW applied by ING Bank to Turkey under the IRB approach in the corporate portfolio was around 34% in 2015, which compares with BNP Paribas' RW of 49%). Importantly, this public dataset also features the NPL ratio for the same portfolio breakdown, thus providing a clear view on the riskiness of obligations.

The results of the paper are aimed at supporting policy discussions held by regulatory authorities, which are currently addressing the complexity and excessive unwarranted variability in the internal models banks use to assess their credit risk. In this context, the paper is meant to shed light on the main determinants of EU banks' risk weights.

Our paper is structured as follows: section 1 and 2 review the literature and the regulatory undertakings aimed at reducing RW heterogeneity. Section 3 then offers an overview of the data used. In section 4, we follow a stepwise procedure, starting with few explanatory variables related to the underlying credit risk to explain RW in a panel econometric approach. First we focus on "*intended* risk weight heterogeneity," and then we analyze whether there is also evidence for "*unintended* risk weight heterogeneity." In section 5, we apply the findings of section 4 and construct hypothetical common equity tier 1 (CET1) ratios for selected banks under the assumption that the banks operate from a different country, while leaving all portfolio characteristics unchanged. Section 6 concludes.

1 Literature on risk weights

Recently, a large and growing body of literature has been exploring topics related to unwarranted RW heterogeneity. On the downside, such cross-country studies often "only" examine banks' risk densities (i.e. the ratio of risk-weighted assets to total assets) at the bank and not at the portfolio level, which is due to the lack of granular data on banks' asset compositions. Vallascas and

[3] *Calculated by means of internal models, risk weights determine banks' minimum capital requirements for credit risk.*

Hagendorff (2013), for example, investigate whether capital requirements accurately reflect portfolio risk by using a cross-country sample of almost 250 listed international banks that covers the period between 2000 and 2010. They conclude that risk-weighted assets based on internal ratings are ill calibrated to, and thus underreport, bank portfolio risk. Beltratti and Paladino (2016) consider a panel dataset of 548 large international banks from 45 countries and use risk densities to test the hypothesis whether banks with higher cost of equity are more aggressive in reducing risk weights. They reject this hypothesis and find that European banks located in peripheral countries did not employ risk-weighted asset (RWA)[4] saving as much as European banks in core countries, where a higher degree of RWA saving was associated with raising more equity during the European sovereign debt crisis. Similarly, by examining a panel of 115 banks from 21 OECD countries, Mariathasan and Merrouche (2014) find that risk densities decline significantly once banks are authorized to apply the internal ratings-based approach to calculate their solvency ratios. To be precise, according to their research, declines in risk weights are more pronounced among weakly capitalized banks. This finding, which is consistent with assumptions about RW manipulation given a weak legal framework for supervision, also applies to countries where supervisors oversee many IRB banks. Using a sample of around 40 banks from the U.S.A., Canada and Europe, Begley et al. (2017) conclude that banks significantly underreport the risk in their trading book when they have lower equity capital. Bruno et al. (2016) explore the drivers of risk-weighted assets among European banks by assessing RW discrepancies of the 50 largest European banking groups between 2008 and 2014. They find that risk weight heterogeneity is explained by the intensity of internal ratings, by bank size, business models and asset mix. In addition, they observe that banks that use IRB approaches more extensively shifted their "riskier" corporate loans to "safer" government bonds from 2008 to 2014.

Besides these cross-country studies, other papers analyze banks' risk modelling within a single country. For example, Behn et al. (2016) investigate a loan-level dataset relating to German banks that use the model-based approach. They show that, first, banks using the IRB approach systematically underpredict actual default rates. Moreover, loss rates are higher for loans under the IRB approach compared with loans under the standardized approach, while RW are significantly lower under the former approach. The most interesting finding is, however, that loans under the IRB approach carried higher interest rates, which suggests that banks were aware of the higher risk associated with these loans. By contrast, Fraisse et al. (2015), who conduct similar research on French banks, report no similar RW manipulations for corporate loans when internal models are used. Along the same lines, Barakova and Palvia (2014) examine U.S. banks and find that IRB RW are determined mostly by portfolio risk, while Plosser and Santos (2014) provide evidence that low-capital U.S. banks try to improve their regulatory ratios.

In June 2017, the IMF published a working paper (Turk-Ariss, 2017) on the heterogeneity of bank risk weights by using the results from the 2015 EBA

[4] *Risk-weighted assets (RWA) are risk weights multiplied by the respective exposure amounts, i.e. amounts given in euro; risk weights per se are measured in percent.*

transparency exercise[5]. Turk-Ariss (2017) finds that corporate RW are influenced by the riskiness of an average representative firm, but not by market averages of firms' probability of default. In addition, she carries out a counterfactual analysis, in which she assigns the same RW to banks operating in a specific country. The counterfactual analysis shows that some banks would experience a significant decline in their capital ratios but still fulfill the minimum capital requirements.

2 Regulatory review of risk weights

In response to the growing literature on RW heterogeneity, regulatory reviews addressed this issue, e.g. the Regulatory Consistency Assessment Programme (RCAP) exercise of the Basel Committee on Banking Supervision, the EBA's review of consistency of risk-weighted assets exercise and the ECB's Targeted Review of Internal Models (TRIM) exercise.

At the beginning of 2016, the BCBS (2016a) consequently proposed changes to the IRB approaches, especially to use model-parameter floors as a key element of the BCBS regulatory reform programs to be finalized by end-2016. The proposed measures aim (1) to reduce the complexity of the regulatory framework and to improve comparability; and (2) to address excessive variability in the capital requirements for credit risk by ensuring a minimum level of conservatism for IRB portfolios. The floor is meant to limit IRB model measurement errors. Moreover, the RCAP exercise resulted in the removal of the option to use advanced IRB approaches for low-default portfolios.

One year later, the ECB (2017) launched on-site inspections in connection with its Targeted Review of Internal Models with a view to (1) improving consistency among banks' IRB methodologies and (2) reducing unwarranted (non-risk-based) variability in RW related to internal models. In a nutshell, the TRIM exercise is meant to ensure that banks' internal models yield adequate capital requirements. Covering all significant institutions with approved Pillar 1 internal models, TRIM includes on-site missions at 68 banks within 15 countries, to be completed by the beginning of 2019. This review covers at least 60% of IRB exposure at default (EAD) for credit risk (equaling some EUR 7 trillion).

In addition, as part of its review of consistency of risk-weighted assets, the EBA (2017a) published a report presenting the results of the supervisory benchmarking exercise for residential mortgages, SME retail, SME corporate and corporate–other portfolios covering 114 institutions in 17 EU countries. According to this report, the country of the reporting bank and the respective countries of the counterparties are important drivers of RW variability. This confirms that RW variability may be due not only to the underlying risk but also to bank and supervisory practices. However, the report also states that on average the estimated values for the probability of default (PDs) and the expected loss given default (LGDs) are higher than the observed default rates and loss rates. In other words, it suggests that banks are in general conservative.

In addition to these supervisory reviews, macroprudential supervision took action to establish RW floors in Belgium, Croatia, Finland, Ireland,

[5] *Our paper is also based on the EBA's transparency exercises, but our time coverage is broader as we include 2012-12, 2013-06, 2014-12, 2015-06, 2015-12 and 2016-06. This allows us to employ panel econometrics and differentiate between time-varying and time-constant effects.*

Luxembourg, Norway, Poland, Romania, Slovenia, Sweden and the United Kingdom. These RW floors apply either on a bank average basis or on an individual loan basis – typically for the asset class of retail mortgages (see ESRB, 2017, for an overview of macroprudential measures).

Both the large and growing body of literature and supervisory as well as macroprudential action attest to the importance of the IRB RW topic.

3 Dataset – EBA transparency exercises

Our analysis is based on the datasets from the EBA transparency exercises. By carrying out these disclosure exercises, the EBA aims to foster market discipline in the Single Market and enhance transparency in the EU banking sector.[6] The three exercises completed to date comprise bank-specific data for six reference dates[7]: representing around 70% of total EU banking assets (European Banking Authority, 2015), the sample consists of over 130 banks, at the highest level of consolidation, from 24 countries in the EU and the European Economic Area (EEA).[8] A considerable advantage of the dataset is its granularity – exposures and RW are broken down by banks, asset classes, the largest countries of counterparty, default status and calculation method (IRB vs. standardized approach) as well as time. This granularity allows us to compare bank-by-bank RW determined by a number of factors.

Given that the data were also partly used in EBA stress tests, both the banks' own and supervisory quality control ensures a high standard of data quality. Needless to say, errors might occur in a dataset that large. To ensure that outliers do not affect our estimates, we exclude observations where RW exceed 370% or where the exposure (of a particular bank to a particular destination in a particular asset class and period) is missing or below EUR 5 million. In general, we consider the data quality to be high.

4 Step-by-step exploration of heterogeneity of risk weights in Europe

4.1 RW comparison based on the standardized and the IRB approach

The first important determinant of the level of RW that we consider is whether the calculation is based on the standardized approach (StA) or the IRB approach. Chart 1.1 below shows kernel density estimates for RW[9] for retail and corporate clients as calculated under the StA or the IRB approach. Chart 1.2 presents a breakdown by the country of the consolidating entity (i.e. the country where a bank is headquartered; in the following referred to as "HQ country"). While StA RW are concentrated around 35%, 75% and 100%, IRB RW populate a broad range of values, all as *intended* by regulation. We infer that IRB RW are substantially lower than StA RW. Moreover, in some countries there is

[6] *The EBA also conducts a benchmarking exercise on a regular basis (EBA, 2017a), which yields more in-depth data. These data are available in full only to the EBA, however.*

[7] *December 31, 2012; June 30, 2013; December 31, 2014; June 30, 2015; December 31, 2015, and June 30, 2016.*

[8] *The number of banks in the sample increased from 64 in the 2013 exercise to 131 in the 2016 exercise (see http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2016/results for more details).*

[9] *We calculate RW as the ratio between "risk exposure amount" and "exposure values" by focusing on non-defaulted exposures as defined by the EBA. For IRB portfolios, the dataset provides the amount of defaulted loans only for the "original exposure," i.e. the exposure before substitution effects. We therefore reduce the exposure after substitution effects ("exposure value") by the share of defaulted loans in the original exposure.*

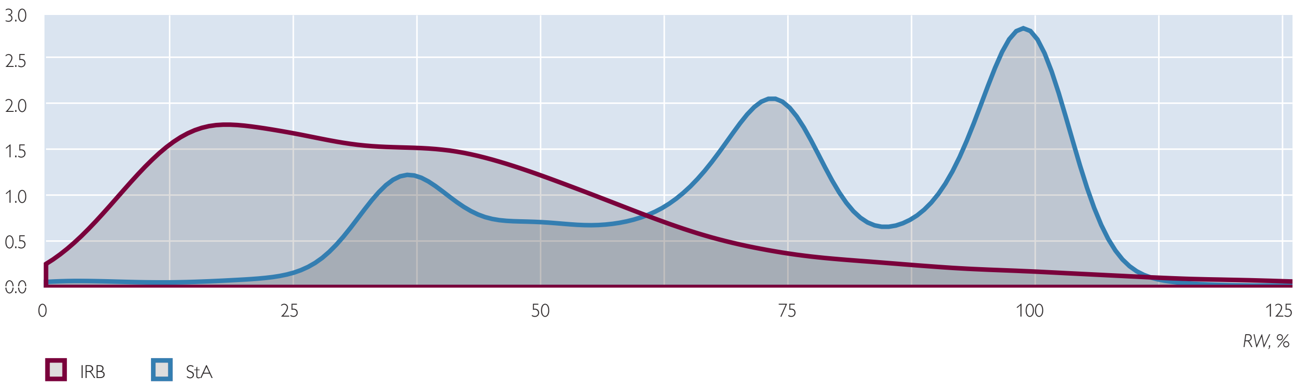
no or hardly any overlap between both distributions. StA RW exhibit a very similar distribution, but IRB RW vary substantially from country to country. For example, Ireland has the highest median RW with a relatively high variation as reflected by the long box plots, while Denmark and Luxembourg have the lowest median IRB RW.

However, several caveats apply to this comparison of StA RW and IRB RW, which makes a more detailed comparison difficult. For one thing, under the IRB approach, banks calculate ex-

Chart 1.1

Comparison: risk weights IRB vs. StA

Density function of RW for corporate and retail exposures

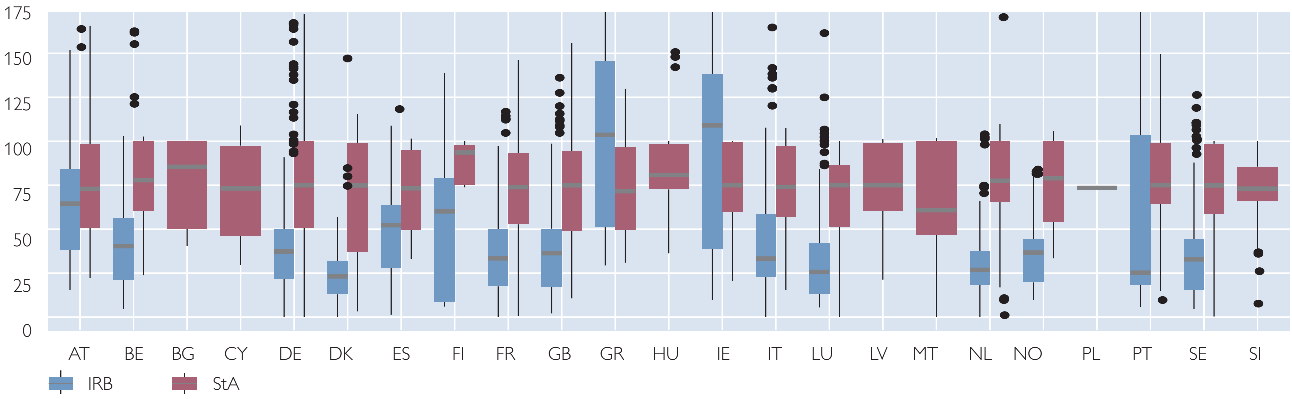


Source: EBA transparency exercises, authors' calculations.

Chart 1.2

Comparison: risk weights IRB vs. StA

RW for corporate and retail exposures per country



Country	AT	BE	BG	CY	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	LU	LV	MT	NL	NO	PL	PT	SE	SI
	Number of observations																						
StA	519	180	12	115	967	135	328	13	739	522	172	127	92	359	120	25	91	343	114	4	294	349	109
IRB	249	247	0	0	959	148	178	39	520	375	25	0	102	235	150	0	0	329	96	0	103	354	0

Source: EBA transparency exercises, authors' calculations.

Note: In countries with a wider box plot, banks calculate RW only under the StA.

pected loss and deduct any excess of this amount over provisions from capital. In addition, the definition of asset classes differs,[10] which likewise makes a more detailed comparison problematic. Given the absence of heterogeneity in StA RW and the above-mentioned lack of their comparability with IRB RW, we decided to focus on IRB RW only. An important takeaway is that, everything else equal, a bank with a higher share of IRB exposures will tend to have substantially reduced RWA. The extent to which a bank uses the IRB approach or StA is therefore crucial to the RW level, but that is beyond the scope of this paper.

In what follows, we limit our sample to IRB RW for the asset classes "corporates," "institutions" and "retail," and we split the latter into "retail – other retail," "retail – qualifying revolving" and "retail – secured by real estate property" to account for the different characteristics in these classes. This leaves us with around 13,900 observations.

4.2 IRB approach: asset classes

To test the importance of asset classes and other determinants of RW (introduced below), we employ a weighted[11] random-effects panel model:

$$y_{i,j,k,t} = \alpha + \beta' X_{i,j,k,t} + u_{i,j,k} + e_{i,j,k,t} \quad (1)$$

where $y_{i,j,k,t}$ denotes the dependent variables (IRB RW) of bank i, to destination country j, in asset class k at time t, $X_{i,j,k,t}$ the explanatory variables, $u_{i,j,k}$ the random effects and $e_{i,j,k,t}$ the idiosyncratic error term. α represents the global intercept and β' the regression coefficients of the explanatory variables. Note that our cross-section is not banks, but a combination of banks, destination and asset class.[12]

A second important factor for the RW level is the asset class, i.e. whether the counterparty is a retail client or a financial institution. Reflecting different risk levels associated with these counterparties, this factor is part of what we described in the introduction as "*intended* risk weight heterogeneity."

In a simple model, this factor alone – asset class – explains already 46% of the variability in IRB RW.

4.3 Bank-specific, portfolio-specific and destination-specific factors

IRB RW are *intended* to be sensitive to the risk of the obligations. Apart from the asset class, we add a range of bank-specific, portfolio-specific and destination-specific factors to capture these effects. If RW solely reflect the risk of the obligations, these factors put together will explain a high share of the variability in RW.

Table A3 in the annex lists the variables that we take into account. The risk of the obligations is determined by the PDs and the LGDs. The risk factors introduced below typically address both the PDs and LGDs simultaneously.

As *destination-specific factors* we use common macroeconomic control variables like GDP growth, unemployment and GDP per capita. These factors account, for instance, for how severe the financial crisis hit the destination

[10] *This is why we keep the comparison between StA and IRB simple by confining it to the broad categories of corporate and retail customers – and even here, differences in the definitions exist.*

[11] *We weight the observations by the exposure amount.*

[12] *The choice of random effects over fixed effects follows automatically from our research question: assuming that RW are determined by the underlying credit risk (an assumption we are evaluating), fixed effects should not be relevant. In what follows, we will introduce dummy effects for destination, time and headquarters, but not for the full set of the cross section (bank, destination, asset class).*

country and whether the latter is an advanced, an emerging or a developing economy. To account for nonlinear effects on default rates as observed in recessions, we also add GDP growth squared (where we maintain the sign). Higher economic growth is associated with fewer defaults, and so are high economic standards and low unemployment. Moreover, in times of economic expansion, it is easier for banks to sell collateral following a borrower's default, which helps limit the LGD.

As bank-specific and portfolio-specific factors we add a dummy variable ("foreign dummy") equal to one if the destination country differs from the bank's HQ. This variable reflects lending to a foreign country, where lending might be more conservative and RW therefore lower. To control for a bank's expertise in lending, we introduce the variable "market relevance." It measures the share of the given portfolio (bank i, destination j, asset class k, time t) in the total credit risk exposure of that bank. A bank concentrating on one particular market and asset class is set to have a high level of expertise in that business area, which is why we expect RW to be lower compared with other areas where lower exposures are likely to go hand in hand with less expertise and higher RW. What is more, the dataset stemming from the EBA transparency exercises allows us to extract the nonperforming loan ratio (NPL ratio) at the same level of granularity (bank–destination–asset class and time level) as an additional control variable. In other words, we can control for the riskiness of banks' individual portfolios. The NPL ratio of a given portfolio captures the share of defaulted exposures,[13] thereby providing a meaningful indicator of an obligor's riskiness.

As banks often pool customers from different countries, we also construct an NPL ratio on a (bank, time and) asset class basis, while disregarding the destination country, as an additional factor. A high NPL ratio signifies both a higher default rate and higher losses because collateral cannot be enforced or has substantially lost value. To the best of our knowledge, we are the first to exploit this feature of granular asset quality.

Taken together, the risk factors discussed above represent a sound set of factors regarding PDs and a decent one regarding LGD. The lack of data on portfolio-level collateral values constitutes a blind spot in an otherwise very comprehensive and granular set of risk factors.

Table 1 presents the estimation results. The first column includes only macroeconomic variables to explain IRB RW. The model output shows that these factors, together with the asset class, explain around 46% of the variability. As expected, both positive GDP growth and higher absolute economic standards (expressed by GDP per capita) reduce IRB RW. When we control for these factors, the level of unemployment no longer has explanatory power. Once we add portfolio- and bank-specific variables (column 2 of table 1), we improve the explanatory power of the model to around 54%. In line with our expectations, higher NPL ratios (both at the single portfolio level and at the asset class level) increase IRB RW,[14]

[13] *Strictly, we have the ratio of defaulted loans. In this paper, "nonperforming" and "defaulted" are used synonymously. There is a slight difference between NPLs and defaulted loans. What we call NPL ratio here is in fact the share of defaulted loans (as included in our dataset).*

[14] *The NPL ratio is a good indicator of the riskiness of the portfolio. Note that the RW are calculated only for the performing portfolio.*

while higher market relevance, used as a proxy for greater expertise, lowers RW.

It is evident from the macroeconomic variables and the coefficients on the NPL ratio that banks will be faced with higher RW during a crisis.[15]

4.4 Adding destination-specific and time-specific hidden effects

Even though the destination-specific and portfolio-specific risk factors considered so far already explain a fair share of RW variability, a substantial

Table 1

Panel estimation results: coefficients and robust standard errors

Variables	Macro	Add risk	Add hidden	Add HQ
Intercept	75.6***	78.1***	77***	81.5***
Unemployment	–0.3	–1.5***	–2.4**	–2.5**
GDP per capita – PPP	–0.5***	–0.4***	–0.4	–0.4
Recent GDP growth	–1.2*	–0.4	0	0
Recent GDP growth squared	0	–0.1	–0.2*	–0.2*
Asset class: institutions	–34 ***	–30.3***	–29.5***	–28.7***
Asset class: retail – other retail	–20.9***	–24.9***	–23.1***	–23.6***
Asset class: retail – qualifying revolving	–20 ***	–22.8***	–22.9***	–24 ***
Asset class: retail – secured by real estate property	–34.6***	–27.7***	–27.8***	–28.5***
NPL ratio		1.1**	1.1**	1.1**
Total NPL ratio per asset class		0.2	0.2	0.2
Foreign dummy		–3.7.	–6.7***	–4.2*
Market relevance		–86.9***	–77.5***	–73.5***
Market relevance squared		103.5***	96.3***	90.2***
June 2013			0.2	0.2
December 2014			–2.4*	–2.5*
June 2015			–1.1	–1.1
December 2015			–1.4	–1.4
June 2016			–1.5	–1.4
HQ in:				
BE				–11.6**
DE				–9.4**
DK				–19.7***
ES				–0.1
FI				–4.8
FR				–7.4*
GB				4.2
GR				–2.6
IE				5.8
IT				–15.5***
LU				–1.3
NL				–9.2*
NO				–9.3.
PT				2.8
SE				–17.2***
R^2	46	54	56	57
Number of observations	7,593	7,593	7,593	7,593
Destination fixed effects	No	No	Yes	Yes

Source: Authors' calculations.

*Note: Codes denoting statistical significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.*

We use HC-robust standard errors.

Reference categories: (1) asset class: corporates, (2) time: December 2012, (3) HQ: in AT.

The dependent variable IRB RW is given in percentage points.

[15] *This cyclicality of RW is discussed e.g. in Kerbl and Sigmund (2009).*

part has yet to be accounted for. One possible explanation may be that there are risk factors specific to the destination country that are not captured by economic growth or other common macro variables but are hidden (at least from our dataset). Besides, RW variability may arise from differences in the portfolio composition. Also, there might be effects across all exposures over time. To account for these, we add a dummy variable for each destination country and time point, which captures all remaining effects common to a destination or a time point. For the results of this regression, see the "Add hidden" column of table 1 and table A5 in the annex.

Indeed, we find that some destination countries (e.g. the Baltics and Slovakia) exhibit higher RW than expected from the macroeconomic and portfolio-specific variables that we control for, while other countries show lower-than-expected RW (e.g. Japan, Ukraine and New Zealand).[16] We conclude that there are country-specific factors common to (a large share of) exposures to these countries that reduce the risk and thereby RW. Once we control for destination- and time-specific effects, some macroeconomic indicators lose their statistical significance, which reflects the usual crowding out of these factors by the more granular fixed effects.

4.5 Adding HQ-specific hidden effects

Having included a comprehensive set of control variables to capture the risk inherent in obligations ("*intended* risk weight heterogeneity"), we can now answer the question whether different implementation standards ("*unintended* risk weight heterogeneity") also play a role. For this purpose, we add dummies depending on the HQ of the bank granting the loan. In an ideal world with equal implementation standards, these HQ fixed effects would not matter, i.e. they would be statistically zero.

The results are displayed in the rightmost column ("Add HQ") of table 1. While the explained variance (R^2) rises only marginally (from 56% to 57%), the HQ effects are important:[17] for most countries we find no significant HQ effects[18], but for some countries[19], there are statistically significant and economically important effects, which is in line with Turk-Ariss (2017) and the EBA (2017a).

The effects are large in Denmark, Sweden and Italy, with low RW due to the HQ of the bank being in these countries, whereas the opposite is true for Ireland, the United Kingdom and Portugal, even though the effects are not statistically significant in the latter countries. As a case in point, the expected IRB RW of a bank headquartered in Italy is 15.5 percentage points lower than the IRB RW of an Austrian

[16] *Looking at the list of destination coefficients (see table A5 in the annex), it is not clear which macroeconomic variables are missing. Many – but not all – Eastern European and less developed countries have higher RW.*

[17] *The probability that all HQ effects are equal to zero can be rejected at any probability level (F-statistic: 228.5 on 16 and 7670 degrees of freedom). The R^2 of using solely HQ effects and no other regressors would be 32%. Chart A2 in the annex provides further evidence in favor of this conclusion.*

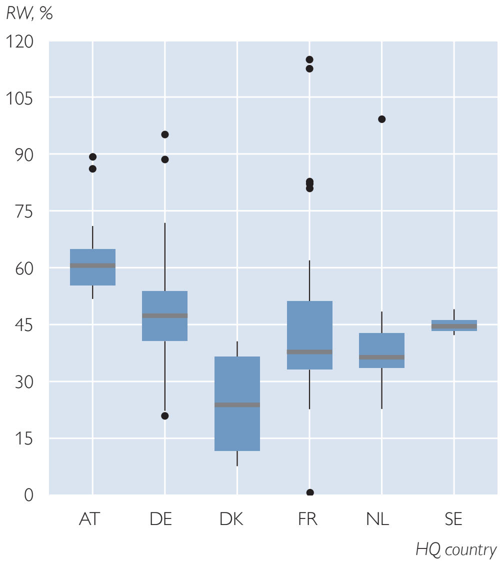
[18] *Note that the sheer number of significant effects depends on the reference category (in this case AT). If we chose the most extreme reference category (the one with the highest effect, IE), the number of significant ($p<0.05$) HQ effects would remain at seven. Also, note that we use HC-robust standard errors.*

[19] *Some of these identified countries have already taken macroprudential measures targeting banks' RW (see http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise/2017 for an overview).*

Chart 2

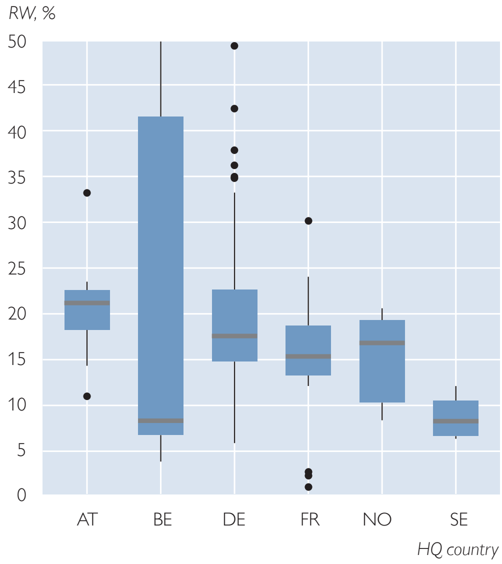
Comparison of IRB RW by HQ country

IRB RW for corporate exposures to DE



Country	AT	DE	DK	FR	NL	SE
No. of obs.	14	78	6	34	16	10
NPL ratio, %	2.53	4.58	0.33	1.79	3.4	1.3

IRB RW for retail exposures to DE



Country	AT	BE	DE	FR	NO	SE
No. of obs.	10	7	50	16	6	6
NPL ratio, %	7.13	6.46	1.19	6.21	0	0.46

Source: EBA transparency exercises, authors' calculations.

bank with the same destination, asset class and macroeconomic environment. These economically important effects would change the CET1 ratio by several percentage points – depending on the share of IRB capital requirements in total minimum capital requirements.

To better illustrate this heterogeneity between HQ countries, chart 2 depicts RW pertaining to the same asset class and the same destination (Germany) of all banks headquartered in selected countries[20]. We see that in some cases RW variability is more pronounced between countries than within one country. In other cases, the medians of the distribution still differ widely. While chart 2 illustrates the heterogeneity across HQ countries, the results of the regression (see table 1) are sharper as the regression allows us to identify HQ effects also after controlling for portfolio-specific NPL ratios.

Here, the question arises whether HQ effects might be driven by different country-specific collateral policies. While this may not be completely ruled out, two facts contest this hypothesis: First, NPL ratios indirectly also provide evidence on collateral, with a highly collateralized portfolio unlikely to remain nonperforming for long. Second, the HQ effects also hold within exposure classes (especially for retail secured by real estate) that exhibit homogeneous collateral requirements within one destination.

Another question is whether the large HQ effects may be in part explained by differences between the

[20] *Germany was chosen as a destination because a large number of banks from different HQ countries actively grant loans to Germany, which enables us to draw this comparison. The HQ countries were chosen based on their HQ regression dummy coefficient.*

advanced and the foundation IRB approach. Under the advanced IRB approach, banks estimate PDs and LGDs, whereas, under the foundation IRB approach, only PDs are estimated, which usually results in higher RW on balance. There are, indeed, cross-country differences in the use of the advanced vs. the foundation IRB approach. The different degrees of advanced IRB usage across countries, however, mainly mirror different degrees of supervisory standards concerning the approval of advanced IRB models, thus falling into the "*unintended* risk weight heterogeneity" category. Against this background, the BCBS (2016a) sees a greater need for reform in the use of advanced IRB models.

Another question is whether data quality issues or data shortages might bias our results. Even in supervisory exercises that collect data dedicated to RW variability, data quality issues are mentioned as a key caveat in the respective findings (European Banking Authority, 2017a, 2017b). As discussed in section 3, the quality controls implemented by banks and supervisors with a view to the data being used in EU-wide stress tests ensure a high data quality standard. The identification of HQ effects separated from (hidden) destination-specific effects depends on cross-border exposures. In general, at 6,362 data points[21], our dataset provides a sufficiently high number of these, which allows us to obtain statistically significant regression coefficients (see table 1). At the same time, such data points may be reported only by a few banks in a given country. For Denmark, for instance, there is only one bank (Danske Bank) with notable cross-border exposures, and only banks from Norway, Ireland and Sweden have cross-border exposures vis-à-vis Denmark. This should be borne in mind when interpreting the regression results. While we need to rely on the given data, we can check the robustness of our results regarding our statistical approach and choices therein.[22]

We perform a number of robustness checks to validate our findings of HQ effects.[23] First, we analyze whether using a pooled OLS estimation would make a difference. Second, we analyze whether dropping destination fixed effects (but maintaining HQ effects) would change the picture. Third, we introduce another variable – rule of law (RoL) – as an indicator of the degree of collateral enforcement. We did not use RoL earlier because of data gaps. To close these gaps to a minimal degree, we assume that Switzerland has the same rule of law as Norway, Slovakia the same as the Czech Republic, Ireland the same as the United Kingdom, and that there are no substantial changes from one year to the next, so if a particular year is missing, we fill this with the adjunct year. Forth, we rerun our estimation without weighting the regression function by the exposure amount. Fifth, we cluster standard errors at the HQ level in order to account for possible correlation in the error terms. Sixth, we use a more detailed breakdown of asset classes (e.g. corporate exposures broken down into SME and non-SME) as previously employed. None of these changes leads to important changes in the HQ effects (for the results, see table A5 in the annex). Also, further regressions conducted in section 4.6 do not change these findings, either.

[21] *These 6,362 data points include only the asset classes studied here, i.e. institutions, corporate and retail.*

[22] *We also checked whether excluding any particular bank in any particular period would change our conclusions, but this was not the case.*

[23] *The results of the robustness checks are shown in table A5 in the annex.*

4.6 Evidence for other "*unintended* risk weight heterogeneity"

In addition to different implementation standards, we look at other forms of "*unintended* risk weight heterogeneity." First, banks with a lower CET1 ratio (e.g. due to an idiosyncratic risk shock) have a greater incentive to push for low RW to artificially increase their CET1 ratio and thereby avoid regulatory and market sanctions. To test this hypothesis, we conduct a two-stage least squares (2SLS) estimation by using the "leverage ratio"[24] as an instrument variable (IV) for the CET1 ratio. In light of the model output, we do not reject our hypothesis that banks with a low CET1 ratio push for low RW, which results in artificial increases of their CET1 ratios. However, this effect is only marginally significant ($p<0.1$). These results (as well as the robustness checks) are shown in table A5 in the annex.

Second, we also test whether large banks are better able to outmaneuver supervisors by increasing the complexity of their models. Large banks tend to have lower RW, but this general observation does not control for asset class composition and other risk indicators discussed above. In our context, we can control for these factors. We add total credit exposure of each bank and/or its log to the regression. We find no statistically significant effect supporting this hypothesis.

5 The effects of changing HQ countries on banks' capital ratios

In this section, we quantify the model results (section 4.5) by assessing how capital ratios – the ratios between capital and risk-weighted assets[25] – would change if we only changed the country where banks are headquartered but kept everything else equal.[26] For this hypothetical prediction exercise, we select the largest banks from every country according to their total credit exposure (both in IRB and StA) and use the estimation results obtained in column "Add HQ" in table 1 to calculate the hypothetical capital ratios. Clearly, these calculations are hypothetical in several respects and should be understood only alongside these caveats: for one thing, we use the point estimates irrespective of statistical significance (e.g. there is also an effect AT vs. IE). For another, we assume that the prediction error is additive and independent of HQ effects. Additionally, total IRB RWA are de facto floored by either 80% of Basel I RWA or standardized-approach RWA. As only banks can calculate these floors, we must ignore this effect and quantify the variability of model-based RW only, i.e. without considering that in some cases floors might kick in.[27] In short, these calculations are meant to illustrate the magnitude of the regression coefficients. The estimates should definitely be taken with a grain of salt:

[24] *As "leverage ratio" we use the ratio of tier 1 capital over total credit exposures.*

[25] *Risk-weighted assets are calculated by multiplying the exposure by the RW. Thus, an increase in RW leads to a decrease in the capital ratio.*

[26] *In this hypothetical scenario, we keep the following elements unchanged: CET1 capital, risk exposure amount for operational risk, for market risk, for credit valuation adjustment and for other risk exposure amounts as well as for credit risk in the StA and for IRB credit risk in the asset class central banks and central governments, equity, securitization, and other non-credit-obligation assets. Moreover, the destination of the counterparties, the NPL ratios in each portfolio and all other predictors remain unchanged. The only thing we adjust is the HQ country.*

[27] *These floors are complicated: whether a bank has to compare its IRB RWA with 80% of Basel I RWA or of standardized-approach RWA is not clear from our dataset. In 2013 (the only year for which data are available), the floor was relevant for only two of the banks represented in table 2: OP-Pohjola Group and Banque et Caisse d'Epargne de l'Etat, Luxembourg.*

Table 2

Hypothetical CET1 ratios for the selected largest banks per HQ country

Bank name	AT	BE	DE	DK	ES	FI	FR	GB	IE	IT	LU	NL	NO	PT	SE
	%														
Erste Group Bank AG	13.3	15.6	15.1	17.5	13.3	14.2	14.7	12.6	12.3	16.5	13.5	15.1	15.1	12.8	16.9
KBC Group NV	13.6	16.7	16.0	19.3	13.6	14.7	15.4	12.7	12.4	18.0	13.9	15.9	15.9	13.0	18.6
Deutsche Bank AG	10.9	12.5	12.2	13.9	10.9	11.5	11.9	10.5	10.3	13.2	11.1	12.2	12.2	10.6	13.5
Danske Bank	10.8	13.3	12.7	15.8	10.8	11.7	12.3	10.1	9.9	14.4	11.0	12.7	12.7	10.3	15.0
Banco Santander SA	12.3	13.7	13.5	14.5	12.3	12.9	13.2	11.9	11.7	14.1	12.5	13.5	13.5	12.0	14.3
OP-Pohjola Group	21.1	27.7	26.6	30.9	21.1	23.6	25.2	19.3	18.7	29.2	21.7	26.5	26.5	19.9	29.9
BNP Paribas SA	10.5	11.7	11.5	12.6	10.5	11.0	11.3	10.1	10.0	12.2	10.6	11.4	11.5	10.3	12.4
HSBC Holdings Plc	12.2	13.5	13.2	14.4	12.2	12.7	13.0	11.7	11.6	13.9	12.3	13.2	13.2	11.9	14.1
Bank of Ireland	14.1	17.2	16.7	18.2	14.1	15.3	16.1	13.2	12.8	17.7	14.4	16.6	16.6	13.5	17.9
UniCredit SpA	9.1	10.1	9.9	11.0	9.1	9.5	9.8	8.8	8.7	10.5	9.2	9.9	9.9	8.9	10.7
Banque et Caisse d'Epargne de l'Etat	17.0	20.9	20.3	23.0	17.0	18.8	19.8	15.6	15.1	22.0	17.4	20.3	20.3	16.0	22.4
ING Groep N.V.	11.3	13.7	13.2	15.9	11.4	12.2	12.8	10.7	10.4	14.7	11.6	13.2	13.2	10.9	15.2
DNB ASA	12.8	15.0	14.5	17.1	12.8	13.6	14.1	12.2	11.9	15.9	13.0	14.5	14.5	12.4	16.4
Banco Comercial Português SA	12.7	14.7	14.2	16.5	12.7	13.4	13.9	12.1	11.9	15.5	12.9	14.2	14.2	12.3	15.9
Nordea Bank Group	11.7	14.7	14.0	17.9	11.7	12.7	13.4	10.9	10.6	16.1	11.9	13.9	14.0	11.1	16.8

Source: Authors' calculations.

Note: The figures in the main diagonal reflect the actual capital ratios, whereas the off-diagonal figures are hypothetical ratios.

parameter uncertainty alone causes these CET1 ratios to fluctuate on average ±85 basis points in a 25%–75% confidence band.

Table 2 shows the hypothetical capital ratios for the largest banks in all countries, with the main diagonal representing the actual capital ratios as at June 2016 and the caveats mentioned above. The off-diagonal elements, which often deviate from the actual ratios, are driven by two factors: (1) the HQ dummy coefficients, and (2) the share of a bank's IRB risk exposure amount in its total minimum capital requirements. While the first factor determines the size of the change to a single RW, the second determines the degree to which a bank's minimum capital requirements are affected. The effects are economically large.

We additionally validate this finding by training a random-forest and a boosted regression tree to our data (see the annex for a description). We then use these models for prediction. Table A1 and A2 in the annex show that capital ratios obtained from the decision trees differ from those obtained from the panel regression (table 2). These differences illustrate that model uncertainty is evident (in addition to parameter uncertainty), again cautioning against taking the figures at face value. The most notable differences are observed for Ireland in the boosted regression tree, where the predicted RW are highest compared with the other models. On the other hand, many predictions are similar to the predictions derived from the random effects model in table 2. For example, Erste Bank's predicted CET1 ratio in the Netherlands would be 15.1% according to the random effects panel model, 15.2% under the random tree method and 14.4% when the boosted regression tree is used.

As there are several cases where the three approaches deviate from each other by more than one percentage point, a narrow interpretation of the results at the bank level is not really meaningful.

In some cases, the identification of HQ effects might be mainly based on banks not listed in table 2[28]. We conclude that, while HQ-specific effects are important, their exact size is subject to model uncertainty.

6 Summary and conclusions

We analyze RW variability in the EU banking sector, using a granular dataset and a panel model approach. Our focus is on the question whether RW can be approximated by observable risk indicators ("*intended* risk weight heterogeneity") or whether there is evidence for "*unintended* risk weight heterogeneity." The latter would reflect differences in banks' and supervisory implementation standards and in banks' propensity to use artificially low internal estimates across jurisdictions.

In a stepwise procedure, we show that a good portion of RW variability can be explained by portfolio- and destination-specific risk indicators such as macroeconomic indicators and NPL ratios. Such variability is in line with regulators' intentions.

We then also study *unintended* variability ("*unintended* risk weight heterogeneity") by analyzing the effects on RW of (1) bank size, (2) bank capitalization, (3) the headquarters country reflecting supervisory practice and implementation standards.

We find that, first, it is not statistically significant that large banks are better able to push RW down (after controlling for the underlying credit risks). Second, it is of marginal statistical significance that banks with low CET1 ratios employ RW that are lower than would be expected from the underlying credit risk.

Third, there are statistically significant and economically important differences relating to the country where the bank is headquartered. This provides evidence that standards are implemented differently from jurisdiction to jurisdiction, a finding that is robust to a range of alternative specifications including tree-based methods.

We conclude that recent efforts by supervisors to lower RW variability are important for market participants, most notably the EBA benchmarking exercise and the ECB's TRIM exercise. With a view to ensuring a level playing field, the measures focusing specifically on the euro area should be extended to encompass also non-euro area countries in order to reduce unwarranted RW variability. Many of the countries with large (negative) HQ effects, i.e. low RW after controlling for risk, have already implemented macroprudential measures that specifically address the issue of low RW. As a case in point, Sweden's financial supervisory authority requires banks to hold systemic risk buffers, to maintain minimum RW and to comply with high capital charges under Pillar 2. In addition, our results support regulatory floors for model outputs as also envisaged under Basel IV and efforts by supervisors to harmonize banks' Pillar III requirements.

Our findings also help inform the ongoing policy debate about the complexity of regulation. Complex rules require a (potentially too) great effort from supervisors to enforce standards consistently and monitor those subject to the rules. It would only be fair that the costs of these efforts were borne by those calling for such complex rules.

[28] *By selecting the largest banks in each country, we addressed this caveat to the extent possible.*

References

BCBS. 2013. Regulatory consistency assessment programme (RCAP) – Analysis of risk-weighted assets for credit risk in the banking book.

BCBS. 2014. Capital floors: the design of a framework based on standardized approaches.

BCBS. 2016a. Reducing variation in credit risk-weighted assets – constraints on the use of internal model approaches.

BCBS. 2016b. Finalising Basel III: Coherence, calibration and complexity. Keynote speech by Stefan Ingves at the second Conference on Banking Development, Stability and Sustainability. 2 December 2016. Santiago, Chile.

Barakova, I. and A. Palvia. 2014. Do banks' internal Basel risk estimates reflect risk? In: Journal of Financial Stability 13. 167–179.

Begley, T. A., A. Purnanandam and K. Zheng. 2017. The Strategic Under-Reporting of Bank Risk. In: Review of Financial Studies 30(10). 3376–3415.

Behn, M., R. Haselmann and V. Vig. 2016. The limits of model-based regulation. ECB Working Paper Series 1928.

Beltratti, A. and G. Paladino. 2016. Basel II and regulatory arbitrage. Evidence from financial crisis. In: Journal of Empirical Finance 39. 180–196.

Bruno, B., G. Nocera and A. Resti. 2016. Are risk-based capital requirements detrimental to corporate lending? Evidence from Europe. CEPR Discussion Paper 12007.

European Banking Authority. 2013. Interim results update of the EBA review of the consistency of risk-weighted assets. August 5.

European Banking Authority. 2015. Report – 2015 EU-wide transparency exercise. 25 November 2015.

European Banking Authority. 2017a. Results from the 2016 High Default Portfolios (HDP) Exercise. EBA Report BS 2017 027.

European Banking Authority. 2017b. Results from the 2016 Market Risk Benchmarking Exercise. EBA Report BS 2017 031.

European Central Bank. 2017. Guide for the Targeted Review of Internal Models (TRIM) – Counterparty Credit Risk. Banking Supervision. February.

European Systemic Risk Board. 2017. National Policy – Other measures. https://www.esrb.europa.eu/national_policy/other/html/index.en.html (retrieved on August 17, 2017).

Fraisse, H., M. Le and D. Thesmar. 2015. The Real Effects of Bank Capital Requirements. HEC Paris Research Paper FIN-2013-988.

Haldane, A. G. 2012. The Dog and the Frisbee. Speech at the Federal Reserve Bank of Kansas City's 366th economic policy symposium "The changing policy landscape." Jackson Hole, Wyoming. 31 August.

Hastie, T., R. Tibshirani and J. Friedman. 2009. The Elements of Statistical Learning. Springer Series in Statistics. New York: Springer.

Kerbl S. and M. Sigmund. 2009. Cyclicality of Regulatory Capital Requirements: First Evidence from Austria. In: Financial Stability Report 18. Vienna: OeNB. 97–106.

Mariathasan, M. and O. Merrouche. 2014. The manipulation of Basel risk weights. In: Journal of Financial Intermediation 23. 300–321.

Plosser, M. C. and J. A. C. Santos. 2014. Banks' Incentives and the Quality of Internal Risk Models. Federal Reserve Bank of New York Staff Reports 704. December.

Turk-Ariss. R. 2017. Heterogeneity of Bank Risk Weights in the EU: Evidence by Asset Class and Country of Counterparty Exposure. IMF Working Paper 17/137.

Vallascas, F. and J. Hagendorff. 2013. The Risk Sensitivity of Capital Requirements: Evidence from an International Sample of Large Banks. In: Review of Finance 17(6). 1947–1988.

Annex

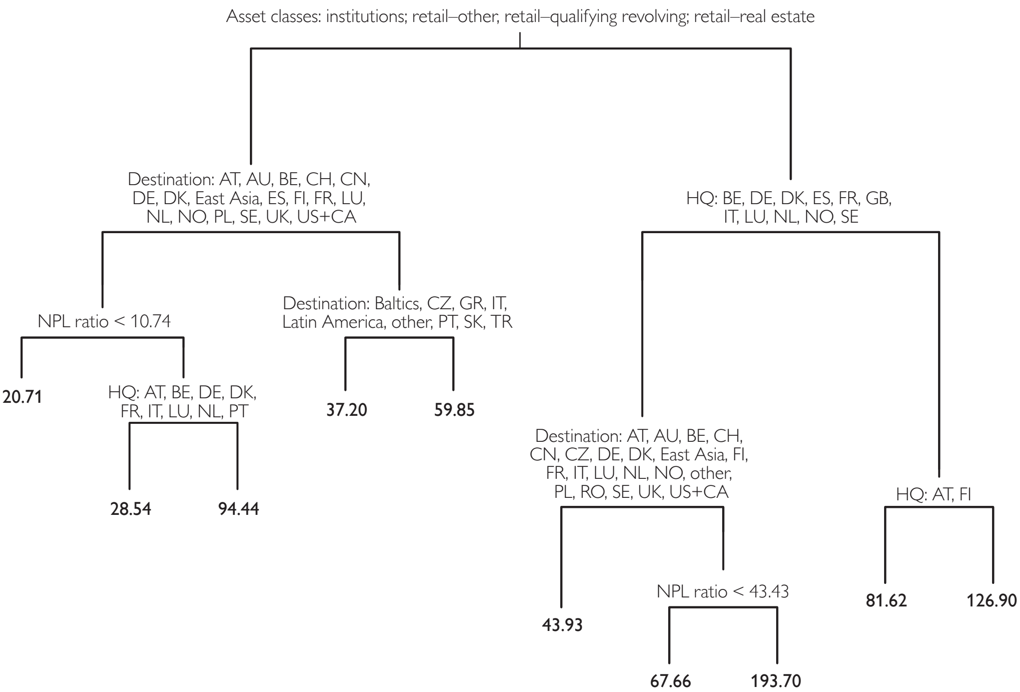
A further method we employ to validate our regression findings is to estimate tree-based regressions explaining RW by the same set of predictors. Specifically, we employ random forests and boosting, flexible and powerful machine learning techniques. A regression tree segments the predictor space into a set of non-overlapping regions in a procedure that minimizes the residual sum of squares at each step. Random forests and boosting both train an ensemble of regression trees that are combined for the final model.[29]

In chart A1, we present one example regression tree for the IRB RW based on the variables used in section 4.5.[30] At every given internal node, both a left and a right branch emanate. For any new observation, follow the tree and go left at each node when the condition is fulfilled and right otherwise.

Even though random forests and boosting differ in the statistical approach from our random panel model employed earlier, the predictions of the model are highly comparable. We also find that – against the intention that only the risk of the obligations drives RW – the location of the headquarters is an important variable in explaining RW (see section 4.5).

Chart A1

Example of a decision tree



Source: Authors' calculations.

Note: If the condition is true, go left down the branch at every split.

[29] *Hastie et al. (2009) provide a useful introduction to these methods in chapters 9, 10 and 15.*

[30] *This method requires us to aggregate destination countries into buckets. The "Baltics" aggregate comprises Estonia, Latvia and Lithuania, while "Latin America" consists of Venezuela, Colombia, Peru, Chile, Brazil and Mexico. Another bucket we construct is "East Asia," which is made up of Japan, Korea, Singapore and Hong Kong. In addition, we treat Canadian exposures and U.S. exposures together. African and island countries are aggregated as "other" countries. This still leaves us with 32 different destination countries.*

Also, to provide for additional robustness checks under section 5, we construct hypothetical CET1 ratios for the largest bank in each HQ country according to the random forest method (table A1) and the boosting method (table A2).

Table A1

Hypothetical CET1 ratios for the selected largest banks per HQ country according to the random forest method

Bank name	AT	BE	DE	DK	ES	FI	FR	GB	IE	IT	LU	NL	NO	PT	SE
	%														
Erste Group Bank AG	13.3	14.6	14.2	15.4	13.7	13.1	14.5	14.0	12.1	15.2	14.4	15.2	14.4	12.4	14.7
KBC Group NV	12.7	16.7	14.9	15.7	14.0	13.4	14.9	14.2	11.8	15.5	15.1	15.9	15.0	12.1	15.9
Deutsche Bank AG	10.0	11.4	12.2	12.3	10.3	9.8	11.6	11.3	9.1	11.9	11.4	12.0	11.5	9.3	12.1
Danske Bank	11.4	14.3	15.6	15.8	12.1	11.3	15.3	13.7	10.2	15.1	14.9	15.2	14.2	10.5	15.7
Banco Santander SA	12.1	12.8	12.8	12.9	12.3	12.1	13.1	12.6	11.2	12.9	13.2	13.0	12.8	11.3	13.0
OP-Pohjola Group	21.5	27.8	27.9	28.1	23.0	23.6	27.2	25.3	20.0	26.9	26.6	27.4	25.4	20.3	30.8
BNP Paribas SA	9.9	11.2	11.2	11.7	10.3	9.6	11.3	10.7	9.0	11.4	11.3	11.6	11.0	9.2	11.4
HSBC Holdings Plc	11.2	12.4	13.0	13.2	11.4	11.1	13.0	11.7	10.3	12.8	12.9	12.9	12.2	10.6	13.1
Bank of Ireland	12.7	14.9	13.2	14.8	14.7	14.1	15.1	11.8	12.8	14.7	15.6	14.7	14.8	12.8	14.6
UniCredit SpA	8.5	9.8	9.6	10.1	9.5	8.7	9.7	8.8	7.4	10.5	10.1	10.2	9.9	8.0	9.8
Banque et Caisse d'Epargne de l'Etat	16.2	19.7	19.9	21.2	17.7	15.2	18.7	18.6	14.9	19.3	17.4	20.8	18.4	14.9	20.6
ING Groep N.V.	11.4	13.1	13.0	13.4	11.9	11.3	12.7	12.6	10.3	12.9	12.7	13.2	12.5	10.5	13.4
DNB ASA	12.8	15.7	15.2	15.4	13.4	13.2	15.3	14.8	11.6	15.0	14.9	15.6	14.5	11.9	16.3
Banco Comercial Português SA	11.7	13.0	11.7	12.8	12.7	12.6	13.0	11.1	11.0	13.1	13.4	13.3	12.9	12.3	12.6
Nordea Bank Group	12.0	15.0	15.5	16.1	12.5	12.3	15.7	13.9	10.6	15.2	15.6	15.5	14.4	11.0	16.8

Source: Authors' calculations.

Note: The figures in the main diagonal reflect the actual capital ratios, whereas the off-diagonal figures are hypothetical ratios.

Table A2

Hypothetical CET1 ratios for the selected largest banks per HQ country according to the boosting method

Bank name	AT	BE	DE	DK	ES	FI	FR	GB	IE	IT	LU	NL	NO	PT	SE
	%														
Erste Group Bank AG	13.3	14.9	14.3	16.0	12.8	10.7	15.2	12.2	9.8	16.0	15.5	14.4	13.8	11.0	14.6
KBC Group NV	13.6	16.7	15.3	17.6	13.6	10.7	16.4	12.8	10.2	17.2	18.0	16.1	14.5	11.7	15.4
Deutsche Bank AG	10.9	11.7	12.2	13.3	11.0	9.9	12.4	11.0	8.8	13.2	12.7	12.2	12.0	9.5	12.4
Danske Bank	11.4	13.2	13.4	15.8	11.7	9.6	14.4	11.6	8.2	14.9	14.5	13.6	14.1	9.1	14.5
Banco Santander SA	12.6	13.0	13.2	14.0	12.3	11.3	13.7	12.0	10.4	14.0	14.2	13.6	13.0	12.0	13.4
OP-Pohjola Group	24.2	30.6	26.7	39.4	24.5	23.6	30.3	23.6	16.4	34.5	34.9	27.7	27.8	19.2	31.1
BNP Paribas SA	10.1	11.0	11.2	11.8	10.3	9.1	11.3	10.1	8.5	11.8	11.6	11.3	11.0	9.2	11.2
HSBC Holdings Plc	11.6	12.2	12.6	13.3	11.5	10.5	12.9	11.7	9.6	13.1	13.0	12.7	12.4	10.3	12.7
Bank of Ireland	14.9	17.7	15.2	19.7	13.9	10.8	17.6	11.4	12.8	17.9	21.9	17.8	14.2	14.9	15.3
UniCredit SpA	8.7	9.8	9.6	10.2	9.0	7.6	9.8	8.2	7.2	10.5	10.5	10.0	9.4	8.1	9.6
Banque et Caisse d'Epargne de l'Etat	15.9	17.9	18.7	20.3	15.2	12.3	18.8	16.0	12.7	19.3	17.4	16.6	17.5	13.2	18.2
ING Groep N.V.	11.7	12.8	13.1	14.6	11.7	10.5	13.6	11.8	9.3	14.1	13.9	13.2	12.8	10.6	13.3
DNB ASA	12.9	14.6	13.9	16.0	12.8	10.6	15.0	12.6	9.7	15.4	14.6	13.9	14.5	10.5	15.4
Banco Comercial Português SA	11.6	15.3	10.8	11.9	12.5	7.9	13.3	9.2	8.2	13.6	12.7	12.8	10.3	12.3	11.1
Nordea Bank Group	13.2	15.5	15.3	18.6	13.3	11.3	16.6	12.9	9.3	17.6	17.2	15.5	15.8	10.6	16.8

Source: Authors' calculations.

Note: The figures in the main diagonal reflect the actual capital ratios, whereas the off-diagonal figures are hypothetical ratios.

Table A3

Description of variables

Variable name	Description	Expected sign	Source
Dependent variable			
Average risk weights for corporate, retail or institution exposures	Ratio between IRB RWA and exposure values (IRB-RW) for corporate, retail (split into retail qualifying revolving, retail secured by real estate property, retail other), or institution exposures[1]	n.a.	EBA transparency exercises, authors' calculations
Destination-specific variables (macroeconomic control variables)			
Recent GDP growth	Average GDP growth rate of past 3 years	–	World Bank
Recent GDP growth squared	Average GDP growth rate of past 3 years squared, where the sign is maintained	–	World Bank
Unemployment	Unemployment rates averaged over past 3 years	+	World Bank
GDP per capita – PPP	Average GDP per capita in terms of PPP in current USD million of past 3 years	–	World Bank
Bank- and portfolio-specific control variables			
NPL ratio	Nonperforming loans over total loans at the portfolio level (bank, destination, asset class)	+	EBA transparency exercises, authors' calculations
Total NPL ratio per asset class	Total NPL ratio per asset class (at the bank and asset-class level only)	+	EBA transparency exercises, authors' calculations
Foreign dummy	Dummy which takes the value 1 if the exposure is cross-border	–	EBA transparency exercise
Market relevance	Share of exposure in total exposure	–	EBA transparency exercises, authors' calculations
Market relevance squared	Share of exposure in total exposure squared	+	EBA transparency exercises, authors' calculations
Total exposure	Total IRB and StA exposure per bank	–	EBA transparency exercises, authors' calculations
CET1 ratio	Common equity tier 1 ratio	–	EBA transparency exercises, authors' calculations
"Leverage ratio"	Share of tier 1 capital in total credit exposure	–	EBA transparency exercises, authors' calculations
Rule of law (RoL)	Overall score of rule of law	–	World Justice Project – rule of law index

Source: Authors' compilation.

Note: Theoretical considerations suggest that the impact of a variable on the risk weight is either positive (+) or negative (–).

[1] To prevent outliers from distorting our estimations, we only consider risk weights smaller than 370% and total exposures greater than EUR 5 million.

Table A4

Summary statistics – descriptive statistics

Variable name	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum	NAs	Standard deviation
Risk weights, %	0	15.32	27.11	35.11	46.55	322.2	0	29.00
Recent GDP growth, %	–6.80	0.36	1.06	1.06	1.91	9.86	77	1.54
Recent GDP growth squared	–46.3	0.13	1.13	2.77	3.63	97.17	77	7.66
Unemployment, %	1.12	2.81	3.59	4.26	4.83	13.14	86	2.38
GDP per capita – PPP, thousands	1.01	37.48	43.56	45.57	49.59	102.1	81	16.59
NPL ratio, %	0	0	0.77	3.73	3.69	100	0	8.35
Total NPL ratio per asset class, %	0	0.40	1.96	3.63	4.44	69.58	0	5.59
Total exposure, 100 billion	0.05	1.56	3.13	5.24	8.68	21.29	0	4.76
Market relevance, %	0	0	0.01	0.03	0.02	0.77	0	0.06
Market relevance squared	0	0	0	0.01	0	0.59	0	0.03
CET1 ratio, %	5.51	11.42	13.01	13.54	15	28.57	0	3.14
"Leverage ratio," %	1.75	4.92	5.50	5.57	6.26	13.45	0	1.12
Rule of law index	0.31	0.72	0.78	0.76	0.81	0.89	220	0.09

Source: Authors' calculations.

Table A5

Panel estimation results: other "unintended risk weight heterogeneity" and robustness checks

Variable	2SLS: CET1 IV leverage	Add size	Add RoL	Pooled	Un-weighted	Add nonlinear NPL	Add asset classes	Clustered SE
Intercept	389.1**	392.1**	85.8***	215.3***	77.6*	366.4**	53.1***	392.2***
NPL ratio	1.1**	1.1**	1.1**	1.6***	0.2*	1.1*	0.7***	1.1.
NPL ratio – nonlinear					0	0		
Total NPL ratio per asset class	0.2	0.2	0.2	–0.3	0.5***	–0.3	–0.2	0.2
Total NPL ratio per asset class – nonlinear					0.1**	0.1**		
Unemployment	–2.4**	–2.5**	–2.7**	–3 *	–1*	–2.8**	–0.3	–2.5
GDP per capita – PPP	–0.4.	–0.4.	–0.4.	–0.3	–0.3	–0.5*	0.1	–0.4
Recent GDP growth	0.1	0	0	–0.2	–3.3***	0	0.1	0
Recent GDP growth squared	–0.2*	–0.2*	–0.2*	–0.2	0.2*	–0.2*	–0.3**	–0.2
Asset class: institutions	–28.7***	–28.7***	–28.5***	–26.7***	–26.7***	–21.6***	–27.3***	–28.7***
Asset class: retail – other retail	–23.5***	–23.6***	–23.4***	–22.5***	–24.6***	–23.8***		–23.6*
Asset class: retail – qualifying revolving	–24 ***	–24.1***	–23.8***	–22.9***	–32.5***	–21.8***	–20.1***	–24.0*
Asset class: retail – secured by real estate property	–28.6***	–28.5***	–28.6***	–29.9***	–33.8***	–27.6***		–28.5***
Asset class: corporates – SME							4.1	
Asset class: corporates – specialized lending							10.5***	
Asset class: retail – other retail – non-SME							–16***	
Asset class: retail – other retail – SME							–18.6***	
Asset class: retail – secured by real estate property – non-SME							–25.8***	
Asset class: retail – secured by real estate property – SME							–23.1***	
Foreign dummy	–4.2*	–4.3*	–4 *	–2.3**	–4.9***	–3.9*	–2.9*	–4.2.
Market relevance	–72 ***	–74.7***	–70.8***	–47.3***	–132.9***	–67.6***	–55.6***	–73.5*
Market relevance squared	87.9***	91.1***	87.1***	57.4***	188.3***	82.6***	63.9***	90.2
CET1 ratio (IV for "leverage ratio")	0.3.							
Total exposure		–0.1						
Rule of law			–22.2.					
June 2013	0.1	0.2	0.2	0.1	3.1***	0.2	–0.1	0.2
December 2014	–2.5*	–2.4*	–2.6*	–3.4.	–0.1	–1.8.	–3.5**	–2.5
June 2015	–1.2	–1.1	–1.2	–2.1	1.2.	–0.3	–3.6**	–1.1
December 2015	–1.4	–1.3	–1.4	–2.3	1	–0.5	–3.9**	–1.4
June 2016	–1.6	–1.4	–1.3	–2.4	1.9*	–0.6	–3.7**	–1.4
HQ in:								
BE	–11.4**	–11.6**	–13.4***	–12.7***	–4.3	–11.8**	–12.3***	–11.6*
DE	–8.9**	–9.3**	–10.9**	–9.7***	–7.3**	–8.5*	–7.8**	–9.4.
DK	–19.5***	–19.6***	–21.2***	–17.4***	–13***	–16.6**	–14.3***	–19.7*
ES	0.3	0.4	–1.6	–0.2	0.5	0.1	3.9	–0.1
FI	–4.6	–4.8	–6.3	–1	5.7	–1.6	–1.5	–4.8
FR	–6.9*	–6.9*	–8.9**	–8.5***	–7.8**	–7.3*	–7.4**	–7.4.
GB	4.6	4.7	2.6	2.9	5.	5.6	7.1*	4.15
GR	–1.5	–2.6	–2	24.5	13.3	–1	17.8	–2.6
IE	4.9	5.9	4	2.8	17.7**	5.8	12.6.	5.8
IT	–15***	–15.2***	–17.1***	–13.7***	–9.6**	–16.3***	–12.9***	–15.5*
LU	–0.7	–1.3	–2.7	–0.3	–10.5**	0.6	2	–1.3
NL	–8.7*	–8.9*	–10.7**	–9.7***	–6.1*	–8.6*	–7.9**	–9.2*
NO	–8.8.	–9.2.	–10.8*	–8.2**	–6.9*	–5.6	–5.2	–9.3
PT	3.2	2.8	1	0.8	7.2	2.4	10.3.	2.8
SE	–16.9***	–17.2***	–18.7***	–15.8***	–9.4**	–13.4**	–14.4***	–17.2*
R^2	58	57	58	65	48	59	59	57
Number of observations	7,509	7,593	7,463	7,593	7,593	7,593	11,328	7,593
Destination fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: authors' calculations.

*Note: Codes denoting statistical significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1. We use HC-robust standard errors except in the rightmost column, where we use clustered standard errors at the HQ level. Reference categories: (1) asset class: corporates, (2) time: December 2012, 3) HQ: in AT. The dependent variable IRB-RW is given in percentage points. 2SLS stands for "two-stage least squares" and SE for "standard error."*

Table A6

Coefficients for destination in "Add hidden" and "Add HQ" regressions

	Add hidden	Add HQ
Angola	325.6*	310.7*
Australia	–9.4*	–8.7*
Barbados	28.8**	22.1*
Belgium	–2	1.7
Brazil	9.8	3.4
Bulgaria	20.2*	13.5.
Canada	7.6	–2.9
Chile	–8.1	–15.2.
China	14.6	4.4
Colombia	8.7	1.5
Croatia	24.9.	19.4
Czech Republic	10.6*	10.5*
Denmark	–3.3	10.5*
Estonia	10.4	21.2*
Finland	5.9	12
France	2.8	4.9
Germany	1.3	5.2
Greece	8.1	5.4
Hong Kong	7.3	–3.5
Hungary	32.2*	29.9*
India	5.5	7.8
Ireland	22.3	14.1
Italy	–0.8	7.2
Japan	–15.5**	–15.7**
South Korea	13.4	14.2
Latvia	34.5**	45.4***
Lithuania	20.9*	31.8**
Luxembourg	17.9	17.8
Mexico	19.8.	12.7
Mozambique	–51	–60.3.
Netherlands	1.7	5.6
New Zealand	–22.5***	–20.5***
Norway	7.3	14.9*
Peru	33.4	25.9
Poland	9.3	10.1
Portugal	15	7.7
Romania	23.8*	17.3
Russia	12.2	13.7.
Saudi Arabia	–8.5	–19.7
Singapore	16.5	7
Slovakia	17.4*	16*
Slovenia	63.2***	56.3***
South Africa	26.3*	16.1
Spain	20.7*	17.4*
Sweden	–5	7.5
Switzerland	–7.9	–8.7
Turkey	18.5.	21.8*
Ukraine	–147***	–150.5***
United Kingdom	2.4	–4.4
United States	11.5*	8.4
Venezuela	2.7	–4.7

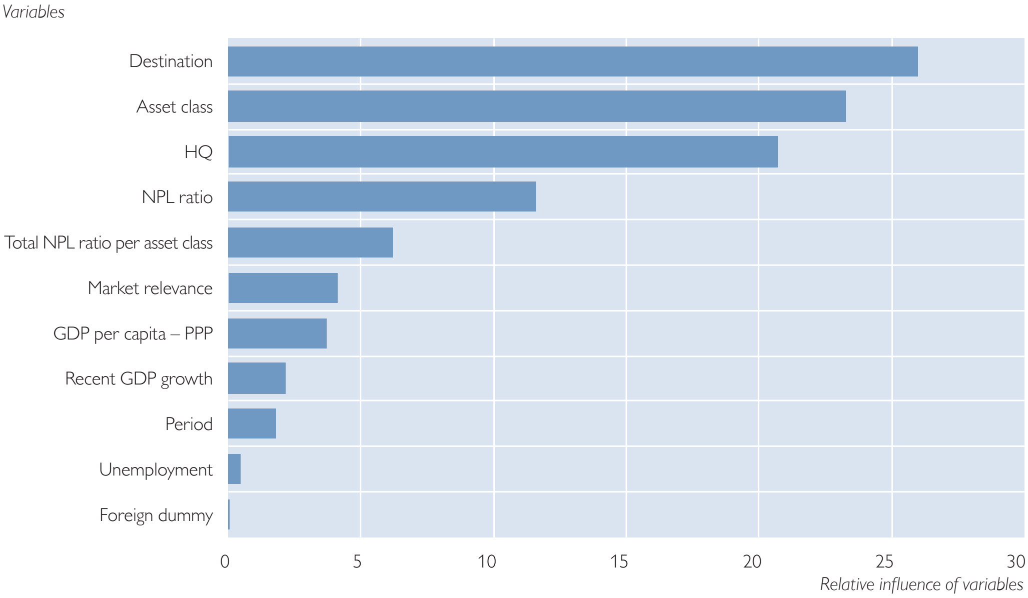
Source: Authors' calculations.

Note: Codes denoting statistical significance:
**** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.*

Table A5 presents the results of section 4.6 ("other unintended risk weight heterogeneity") in the first two columns ("2SLS: CET1 IV leverage," "Add size"). The other columns present robustness checks described in section 4.5. The column entitled "Add NPL nonlinear" adds PD indicators where the NPL ratios are transformed according to the risk weight formulae in Article 153 CRR (with LGD=0.45 and M=2.5).

Chart A2

Relative influence of variables according to the boosting method



Source: EBA transparency exercises, authors' calculations.