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Risk and Risk Weights

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Abstract

This paper studies the relationship between the riskiness of banks' assets and their average risk weight. Banks' initial risk weights explain about half of the variation in projected credit losses in the 2018 European Banking Authority stress test. In contrast to related papers, this paper also shows a statistically and economically significant relationship between risk weights and estimates of banks' asset volatilities based on market data. However, I also find issues with risk weights as measures of risk. They do a worse job of explaining future credit losses than do asset volatilities, especially in the case of banks using internal models.

Resume

I dette papir undersøges forholdet mellem risikoen på bankernes aktiver og deres gennemsnitlige risikovægt. Bankernes risikovægte forklarer omkring halvdelen af variationen i kredittab i Den Europæiske Banktilsynsmyndigheds 2018 stresstest. I modsætning til beslægtede papirer viser dette papir også et statistisk og økonomisk signifikant forhold mellem risikovægte og estimaterne af bankers aktivvolatiliteter på grundlag af markedsdata. Der er dog også problemer med at bruge risikovægte som mål for risiko. De er ikke lige så gode til at forklare fremtidige kredittab, som volatiliteten i aktiver er. Det gælder især for banker, der gør brug af interne modeller.

Key words

Financial regulation; stress tests; credit risk.

JEL classification

G20; G28.

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The authors alone are responsible for any remaining errors.

Risk and risk weights

Søren Korsgaard*, Danmarks Nationalbank

November 2019

Abstract

This paper studies the relationship between the riskiness of banks' assets and their average risk weight. Banks' initial risk weights explain about half of the variation in projected credit losses in the 2018 European Banking Authority stress test. In contrast to related papers, this paper also shows a statistically and economically significant relationship between risk weights and estimates of banks' asset volatilities based on market data. However, I also find issues with risk weights as measures of risk. They do a worse job of explaining future credit losses than do asset volatilities, especially in the case of banks using internal models.

Keywords: Banks; Capital Requirements; Stress Testing

JEL-classification: G20; G28

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1. Introduction

Risk weights enjoy a less-than-stellar reputation. As part of the denominator of banks' capital ratios, they play a central role in the determination of whether banks are adequately capitalized or not. But they are frequently characterized as faulty measures of risk which are prone to "gaming". Banks which are permitted to use internal ratings based [IRB] models can themselves estimate some of the parameters that feed into the risk weight formula. This creates model risk and may lead banks to tweak internal models to ensure lower capital charges.

To counter these risks, the final Basel III rules include a minimum leverage ratio based on unweighted exposures, and input and output floors limiting the reduction in capital requirements banks can derive from using internal models. The potential problem is that these changes will make banks' capital requirement less risk-sensitive if risk weights reflect actual risk. Much of the existing literature suggests that this is a big "if".

This paper offers a more sanguine view of the role of risk weights. Based on the results of the 2018 European Banking Authority [EBA] stress test, I show that banks' initial risk weights explain about half of their projected credit losses under stress. Banks' own credit loss projections are therefore consistent with their risk weights. This may be explained by banks using the same or similar models to calculate the parameters (such as probability of default and loss given default) that feed into the risk weight formula and impairment projections. However, the same finding applies if one compares average risk weights to estimates of asset volatilities based on realized equity volatilities. Banks with lower average risk weights also have lower asset volatilities.

A bank's average risk weight, the ratio of its total risk-weighted assets to its total assets, is referred to as a "risk weight density" in the literature.[1] I show that, controlling for risk, banks using internal models have lower risk weight densities than those using the standardized approach to calculate capital requirements, and risk weights increase more as a function of asset volatility for banks using internal models. Both of these findings are

[1] A bank's total risk-weighted assets are also referred to as its risk exposure amount.

consistent with what one should expect to find, given that risk weights are less granular under the standardized approach and that banks using the standardized approach tend to have riskier assets.

The results of the paper are somewhat surprising, including to its author, since the related literature is generally critical of risk weights as a measure of risk. For example, Acharya et al. (2014) compare the results of regulatory stress tests with those of a market-based stress test, and find that the outcomes of their market-based stress tests are more highly correlated with regulatory measures of capital shortfall when these are based on unweighted rather than risk-weighted assets. Looking at German loan-level data for corporates, Behn et al. (2016) show that loans originated by banks using IRB models have lower risk weights than loans originated under the standardized approach, but higher ex-post default rates. Other studies look at and find inconsistencies in how different banks rate the same loans (Berg and Koziol, 2017; Firestone and Rezende, 2016).[2] Finally, some studies present evidence suggestive of risk weight manipulation (Ferri and Pesic, 2017; Mariathasan and Merrouche, 2018).

The idea of comparing risk weights to estimates of asset volatilities is not novel to this paper. Vallascas and Hagendorff (2013) similarly look at the relationship between risk weight densities and asset volatilities. They estimate asset volatilities from market data using the Merton (1974) model, as do Das and Sy (2012). These papers only find weak relationships between risk weights and asset volatilities. Montes et al. (2018) also look at the relationship between risk weights and market-based measures of risk, for example equity volatility and CDS spreads, and they likewise do not find a strong relationship.

There are examples of papers which find positive effects of using internal models. Cucinelli et al. (2016) find evidence of stronger risk management practices among banks using internal models, while Barakova and Palvia (2014) show a high correlation between loan performance and risk parameter estimates from internal models. Further related literature includes Colliard (2019), who discusses the general trade-off between having risk-sensitive capital re-

[2]The European Banking Authority also conducts an annual assessment of variability in risk weights across banks. They find that most of the variability can be explained by observable features of the banks' exposures.

quirements and the risk of regulatory arbitrage in a theoretical setting, and Baule and Tallau (2016) who look at, among other things, the cyclicality of banks' risk weights.

How to reconcile the difference in results between this and related papers? A useful starting point is to consider the risk weight formula.[3] In the risk weight formula, risk weights depend on - they are literally a function of - the Basel risk parameters such as the probability of default. In credit risk models, default probabilities can themselves be described as functions of asset volatilities. In the paper I derive a stylized theoretical relationship between risk weights and asset volatilities. This is accomplished by combining the model that underlies the risk weight formula with a simple structural model of a bank's assets similar to that in Nagel and Purnanandam (2019). The key insight from the derived theoretical relationship is that all of the information in the Basel parameters is essentially embodied in the bank's asset volatility.

Perhaps equally importantly, the theory also tells us that risk weights should not depend on a host of other factors. It is commonplace to see risk weight densities explained as a function not only of asset volatilities, but also a host of other bank characteristics (e.g. profitability, ratio of deposits to loans or liabilities, etc.). But we know that these variables should not affect risk weights, since they are not part of the risk weight formula. Moreover, since these characteristics are most likely themselves related to a bank's risk profile, they are "bad controls": Their inclusion is likely to remove much of any true effect of asset risk on risk weights. As one example, Vallascas and Hagendorff (2013) include banks' return on assets and their funding structure as controls, even though these variables might themselves be the outcomes of a bank's risk profile.[4]

The failure to find a relationship between risk weights and a number of market-based measures of risk can also be explained. While there ought to be a relationship between

[3]Here I refer to the risk weight formula for credit risk exposures. Throughout the paper I focus on credit risk since this risk type accounts for the bulk of most banks' risk-weighted assets.

[4]They also include the lagged value of average risk weights in their specification. Now, if both present and lagged risk weights are functions of asset volatilities and average risk weights are less variable than asset volatilities - and they should be, since risk weights depend on through-the-cycle parameters to avoid procyclicality - much of any true relationship between risk weights and asset volatilities is going to be captured by the lagged term rather than by the asset volatility itself.

risk weights and asset volatilities, the same is not true if one instead looks at risk measures which reflect embedded leverage. Banks whose underlying assets have low volatilities - and low risk weights - tend also to be more highly leveraged. These banks may therefore be just as risky investments as banks with riskier assets, but lower leverage, and this is reflected in risk measures such as equity volatilities and CDS spreads.

The rest of the paper proceeds as follows. In Section 2, I look at the relationship between risk weights and credit risk losses in the EBA 2018 stress test. Before proceeding to the empirical analysis of the relationship between asset volatilities and risk weights, I derive a theoretical relationship between these quantities in Section 3. The empirical analysis follows in Section 4. Section 5 concludes.

2. Risk weights and credit losses: Evidence from the EBA 2018 stress test

The EBA regularly conducts European-wide stress tests. The 2018 stress test covered 48 of Europe's largest banks. The EBA stress test is a so-called "bottom-up" stress test. This means that banks themselves make the calculations using their internal models. However, the banks are required to follow common methodological assumptions, and their reported results are subject to quality checks by supervisory authorities. Granular bank-level data on the outcome of the stress test is available from the results section of the EBA's website.[5]

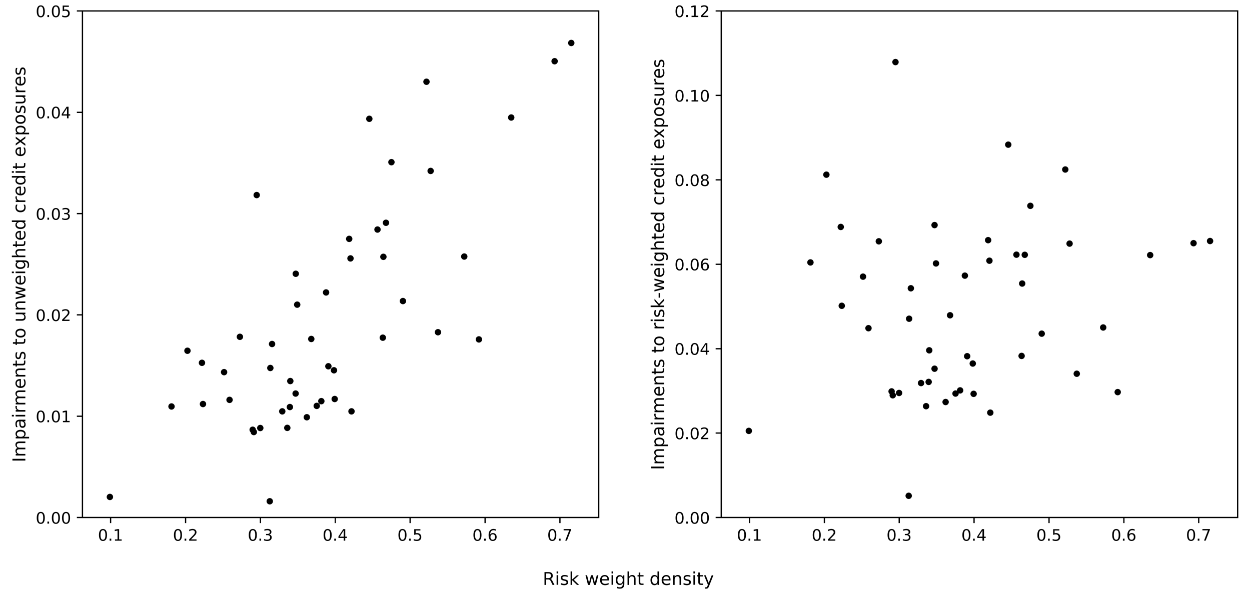
The adversity of the scenario varies from country to country, sometimes considerably. In the adverse scenario of the 2018 stress test, for example, GDP is assumed to fall by more than 10 percentage points in Sweden, but less than 1 percentage point in Poland and Spain.

In the stress test, most banks suffer declines in their capital ratios. The aggregate results show credit risk losses to be by far the largest source of this decline, followed by changes in risk weights (which likewise are the result of changes in credit risk).[6]

[5] https://eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2018/results

[6] This is evident from the EBA's published aggregate waterfall charts which include a decomposition of the change in capital ratios over the course of the stress test.

Figure 1: The figure shows the relationship between risk weight densities, here defined as the ratio of a bank's initial (i.e. prior to the stress test) credit risk-weighted assets to total credit exposures, and total impairments over the stress horizon (2018-2020) divided by total credit exposures [left panel] and risk-weighted credit exposures [right panel]. The data are from the 2018 EBA stress test and covers 48 banks.



As shown in section 3, risk weights reflect tail-risk default probabilities. One should therefore expect credit risk losses in a stress test, itself a tail event, to be correlated with risk weights.

Figure 1 [left panel] shows a clear relationship between risk weight densities and the ratio of credit risk losses (impairments) to total (unweighted) credit exposures. The relationship disappears, as one should expect, when average risk weights are plotted against credit risk losses to risk-weighted exposures [right panel].

Since figure 1 only shows the relationship between risk weights and credit losses, it could mask other factors such as the adversity of the scenario. For example, the positive relationship between risk weight densities and credit losses could be due to the scenarios being more adverse in countries where banks also tend to have higher risk weights. In table 1 I control for changes in the unemployment rate, GDP, and residential house prices. It is not obvious whether one should look at changes relative to the starting point or to the projected baseline scenario. Spanish house prices, for example, are assumed to fall by 14.3 per cent relative to the starting point, but by 25.8 per cent relative to the trajectory in the baseline scenario, in which house prices are assumed to grow by approximately 15 per cent over the period. In practice, though, whether one controls for absolute or relative changes does not affect the results.

Table 1: This table shows regression results of credit losses on risk weight densities and macroeconomic variables from the adverse scenario of the 2018 EBA stress test. Credit losses are defined as total impairments over the stress test period (2018-2020). The risk weight density is here defined as the ratio of a bank's initial (i.e. prior to the stress test) credit risk-weighted assets to total credit exposures. The macroeconomic scenario controls are separately included in absolute terms, i.e. deviations from the starting point, and relative terms, i.e. deviations relative to the projections in the baseline scenario. Standard errors of the estimates are in parenthesis. Robust standard errors in parenthesis are clustered by country. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

	No scenario controls	Absolute changes	Relative changes
Risk weight density	0.064***	0.065***	0.066***
	(0.009)	(0.011)	(0.009)
Unemployment		0.147*	0.250***
		(0.073)	(0.082)
GDP		0.019	-0.025
		(0.100)	(0.041)
House prices		-0.016	-0.005
		(0.018)	(0.014)
N	48	48	48
Adj. R^2	0.540	0.551	0.588

Banks' own projections of credit losses are highly correlated with their risk weights. In fact, risk weights explain more than half of the variation in credit losses. That is a comforting result. Both impairments and risk weights depend on the same Basel risk parameters, and it would be a cause for concern if risk weights did not help forecast credit losses under stress. The more curious feature of the results in table 1 is that scenario adversity adds so little explanatory power.[7]

The analysis also indicates that risk weights can be used by supervisory authorities as a simple tool to check consistency in impairment projections across banks in stress tests and for outlier detection. If a bank's impairment projections deviate from what one would expect based on its risk weights, it may be a cause for concern if the deviation cannot be explained by other factors (e.g. related to the scenario).

[7] For each bank I have added the scenario variables of each bank's home country. For banks with a large international presence the scenario variables may therefore be a somewhat inaccurate representation of the scenario adversity facing these banks.

3. Asset volatility and risk weights in theory

While the previous section showed a clear correlation between banks' risk weights and their projected credit losses under stress, this does not necessarily establish a link between risk weights and risk. If banks use the same or similar internal models to calculate risk weights and impairments under stress, both calculations might suffer from the same (model) failures to capture risk. In the following I therefore look at an alternative gauge of risk: estimates of asset volatility.

There are two steps in this process. The first is to think about how risk weights ought to be related to asset volatility. This helps sharpen our thinking about how to - and how not to - identify a relationship between risk weights and asset volatility. The second is to estimate the volatility of a bank's assets.

A useful starting point is the risk weight formula itself, which has its origins in the work of Vasicek (1987, 1991). The underlying model assumes that bank loans are subject to idiosyncratic (Z_i) and systematic (F) factors, both standard normal. If the realizations of these factors are sufficiently unfavourable and a threshold (t_i) is breached, default occurs. A correlation parameter (ρ) determines the weight of each factor. Concretely, default occurs if

$$\sqrt{1-\rho^2}Z_i + \rho F < t_i, \quad Z_i \sim N(0,1), \quad F \sim N(0,1). \tag{1}$$

The unconditional default probability (PD_i) is therefore

$$PD_i = Pr\left(\sqrt{1-\rho^2}Z_i + \rho F < t_i\right) = N(t_i). \tag{2}$$

It follows that the threshold itself is then defined by the default probability $t_i = N^{-1}(PD_i)$. In practice the default probabilities of loans are estimated by means of other statistical models, e.g. logistic regressions, and then used as inputs in the risk weight formula.

Banks are required to hold capital against unexpected (far in the tail) losses. In the Basel risk weight formula this is achieved by using default probabilities conditional on a highly unfavorable realization of the systematic factor, specifically $F = N(0.001) = -N(0.999)$.

The conditional default probability is

$$Pr\left(\sqrt{1-\rho^2}Z_i + \rho F < t_i \mid F = -N^{-1}(0.999)\right) = N\left(\frac{N^{-1}(PD_i) + \rho N^{-1}(0.999)}{\sqrt{1-\rho^2}}\right). \quad (3)$$

This expression is directly present in the risk weight formula with risk weights being proportional to the difference between the conditional and unconditional default probabilities, i.e.

$$RW_i \propto N\left(\frac{N^{-1}(PD_i) + \rho N^{-1}(0.999)}{\sqrt{1-\rho^2}}\right) - PD_i. \quad (4)$$

However, we care about the relationship between risk weights and asset volatilities, not default probabilities. To get an idea of this relationship - in a stylized fashion - we can combine the above with a simple structural model of a bank's assets such as that in Nagel and Purnanandam (2019). The model assumes that creditors' underlying assets (A_i), or the collateral supporting a loan, follow a geometric Brownian motion, as before with idiosyncratic (X_t^i) and systematic components (W_t). A key parameter then is how volatile (σ_A) these assets are. Letting δ be a correlation parameter, the process for the assets is assumed to be

$$\frac{dA_t^i}{A_t^i} = rdt + \sigma_A\left(\sqrt{1-\delta^2}dX_t^i + \sqrt{\delta^2}dW_t\right), \quad (5)$$

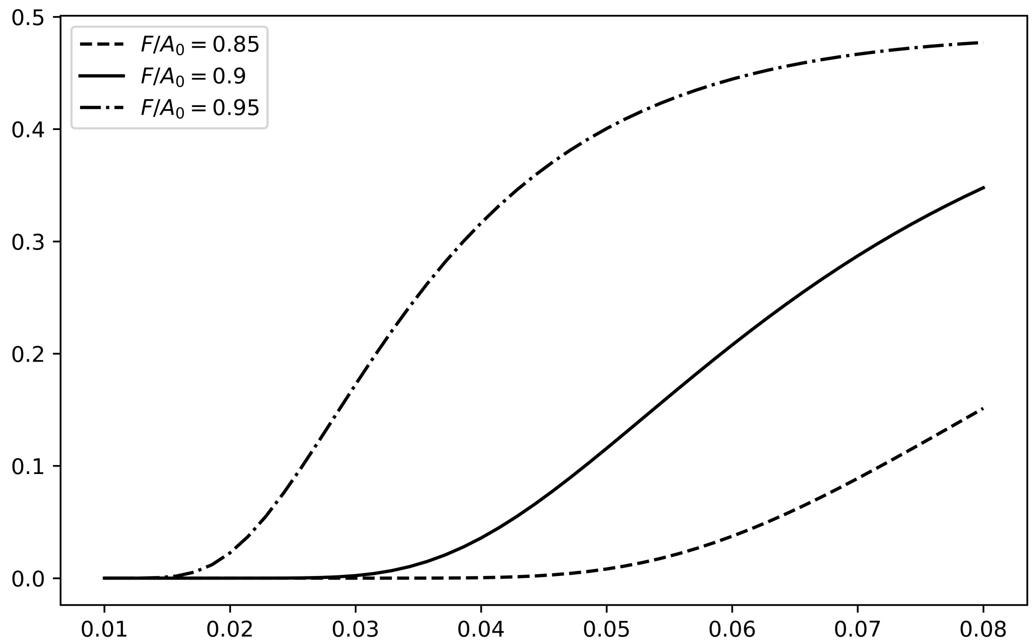
which implies

$$A_T^i = A_0^i e^{(r-0.5\sigma_A^2)T + \sigma_A\left(\sqrt{1-\delta^2}X_T^i + \sqrt{\delta^2}W_T\right)}. \quad (6)$$

If default occurs when the asset process reaches a threshold, K, which one can think of as the face value of the loan, and we take $T = 1$, then the unconditional default probability is

$$PD_i = N\left(\frac{1}{\sigma_A}\left(\ln\left(K/A_0^i\right) - \left(r - 0.5\sigma_A^2\right)\right)\right). \quad (7)$$

Figure 2: The figure depicts a stylized relationship between asset volatility (σ_A) and risk weights described in equation 8 for different values of the ratio K/A_0.



We can then combine equations (4) and (7) to get[8]

$$RW \propto N\left(\frac{\frac{1}{\sigma_A}\left(\ln\frac{K}{A_0^i} - (r - 0.5\sigma_A^2)\right) + \rho N^{-1}(0.999)}{\sqrt{1-\rho^2}}\right) - N\left(\frac{1}{\sigma_A}\left(\ln\frac{K}{A_0^i} - \left(r - 0.5\sigma_A^2\right)\right)\right). \tag{8}$$

The relationship between asset volatility and risk weights is illustrated in figure 2 for different values of the ratio K/A_0.

One obviously should not take the exact functional relationship between risk weights and asset volatility described above too seriously. It is derived based on a stylized model and simplifying assumptions and is intended for illustrative purposes mainly. The formulas do, however, help us think about the relationship between risk weights and asset volatility. Risk

[8]Here I am simplifying. In reality, the correlation coefficient, ρ, in the risk weight formula as well as a maturity adjustment term are also functions of PD, and for simplicity I am ignoring this.

weights are ordinarily an increasing function of asset volatility.[9] The relationship need not be linear, and it tends to be flat for very low risk assets because default probabilities are very close to zero for these assets and remain too close to zero for small changes in asset volatilities.

The above can be taken one step further. The volatility discussed above, σ_A, is the volatility of the creditors' assets. This is not the same as the volatility of the bank's assets, but the two are related. The payoff profile of a loan is similar to the payoff profile of a short position in a put option. The bank receives $\min\{A, K\} = K - min\{A - K, 0\}$, and the volatility of this payoff will be a function of both σ_A and the ratio of K to A, the other important determinant of the risk weight in (8). This ratio is also related to loss given default.[10] This shows that the key Basel parameters, which feed into the risk weight formula, are also reflected in the asset volatility.

Equally importantly, the risk weight formula tells us that one should not "explain" risk weights by including a host of other factors. Indeed, any number of bank variables whether related to profitability, funding structure, etc. are themselves likely to be related to the risk of a bank's assets. They are therefore "bad controls" (Angrist and Pischke, 2009). If included, part of any true effect of asset volatility is likely to, inadvertently, be captured by those variables.

Perhaps the main challenge is to estimate the asset volatility. A standard approach in literature, including in related papers, is to solve the following equations for σ_A and A:

$$E = AN(d_1) - e^{-r}DN(d_2) \tag{9}$$

$$\sigma_E = N(d_1)\frac{A}{E}\sigma_A. \tag{10}$$

[9]Ordinarily, but not always: If the ratio K/A_0 is close to or above one, in which case a loan is highly likely to be defaulted upon, the functional form might look quite different. This is because very high risk loans have low risk weights: Risk weights are designed to cover unexpected losses, but expected losses therefore are not unexpected - rather, they should already be covered by impairment charges.

[10]For example, in the case of a mortgage it can be interpreted as a loan-to-value ratio.

where $d_1 = \frac{1}{\sigma_A}\left[\ln\ A/D + (r + 0.5\sigma_A^2)\right]$ and $d_2 = d_1 - \sigma_A$.

These equations follow from the Black-Scholes-Merton option pricing model. A denotes the market value of a bank's assets, D the value of its debt, E the market value of equity, r the risk-free rate, and σ_A the asset volatility and σ_E the equity volatility. The time to maturity has been set to 1 in the above equations.

This approach is not entirely innocuous. One could argue on theoretical grounds, as Nagel and Purnanandam (2019) do, that the assumption of describing a bank's assets as following a geometric Brownian motion does not make sense - since a geometric Brownian motion implies an unlimited potential upside, but typical bank assets such as loans have limited payoffs - or that using risk-neutral valuation principles is dubious when the firms' total assets are not traded. Another line of critique might be that the market value of a bank does not only reflect the nature of its current assets (as risk weights do), but also to a large extent its future franchise value. From a practical point of view, though, the key issue with the Merton model seems to be that is produces unintuitive results for banks with high valuations (say, measured by the ratio of market to book equity). Since option prices are an increasing function of asset volatility, the model tends to output unusually high asset volatilities for the most valuable banks, when those high valuations often seem more likely to stem from other factors than particularly risky assets. If one calculates the average estimated asset volatility and average market-to-book ratio of equity for each bank, the correlation between these is 0.79. (In comparison, the correlation between market-to-book ratios and average equity correlation is -0.11.)

However, one should not discount market information. Atkeson et al. (2017) show that the inverse of the equity volatility - which they show to be a useful approximation of distances to default/insolvency - does a good job of summarizing both financial and non-financial firms' financial soundness. To also incorporate leverage information, which reflects the current assets of a bank, I take the pragmatic approach of dividing the equity volatility by book leverage rather than market leverage. I therefore estimate asset volatility as

$$\sigma_A = \frac{E_{book}}{A_{book}} \sigma_E^{realized}. \tag{11}$$

This incorporates both a leverage dimension and equity volatility. The choice of book leverage can be justified on the grounds that the book value of assets may be a better approximation of the value of the bank's current loans than the market value which, as mentioned, reflects factors beyond the assets in place. Another way to motivate the choice is by looking at correlations with other measures of asset risk. The correlation between banks' average impairment rates over the sample (see the following section for a description of the data) and asset volatility as calculated above is 0.68; the same correlation but with asset volatilities derived from the Merton model is 0.39.

I calculate equity volatilities for each bank in each year based on weekly equity returns in the +/- 26 weeks around a data point.

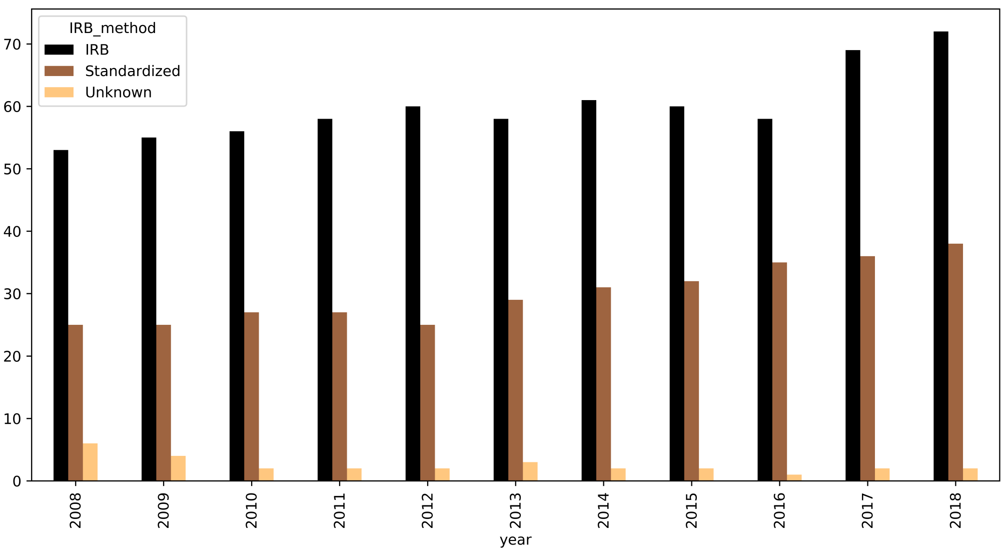
4. Risk versus risk weights

In this section I look at whether risk weights reflect asset risk, as measured by the asset volatility as calculated in equation (11). The data set used in the analysis covers European banks over the period 2008-2018 and has been collected from S&P Global Market Intelligence. It includes only listed banks which are relatively frequently traded. Specifically, banks whose week-to-week stock returns are zero in more than 10 per cent of all weeks have been discarded from the data set.

The lowest risk (asset volatility) banks in the data are Swiss cantonal banks, which are partly government-owned. I exclude these, because the low estimated volatilities are likely to be affected by their ownership structure. I also exclude the two banks with the lowest average risk weights, comdirect bank AG and FinecoBank, whose assets seem to mainly consist of loans to their parent banks.

In total, 114 banks are included in the data set. The majority of these use internal models. The distribution over time by model approach is shown in figure 3. I define banks

Figure 3: The figure shows the number of banks in the data set which are classified as using internal models ("IRB"), a standardized approach, or for which no classification is available for each year in the period 2008-2018. Banks are defined as IRB banks if their approach to the calculating capital requirements is classified as either "Advanced IRB", "Foundation IRB" or "Mixed". The data are from S&P Global Market Intelligence.



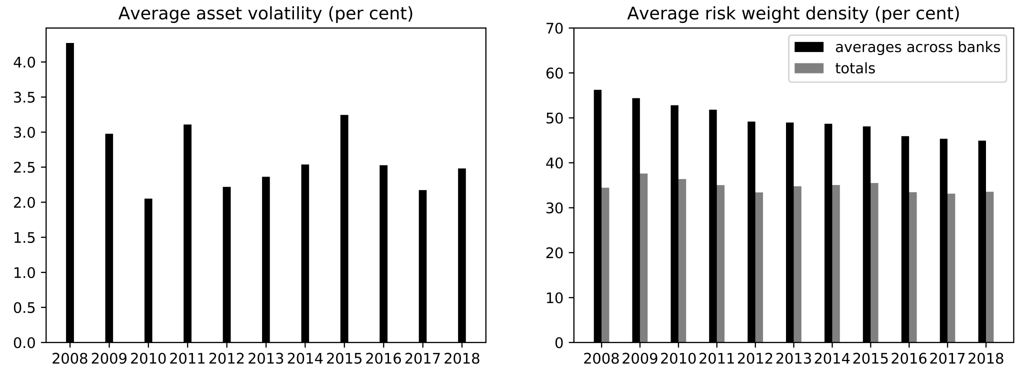
as being IRB banks if their approach to calculating capital requirements is classified as either "Advanced IRB", "Foundation IRB" or "Mixed". "Mixed" is the most prevalent classification among IRB banks.

The estimated asset volatilities vary considerably from year to year whereas the average risk weights change only gradually, as shown in figure 4. The right panel in the figure shows both the average *across* banks (in black), which shows a gradual decline, and the ratio of total risk-weighted assets to total assets summed over all banks (in grey) for each year, for which it is harder to discern any pattern.

The key object of interest is how asset volatilities are linked to risk weights. When risk weights are not particularly cyclical, it is partly by design. Banks are encouraged to use through-the-cycle parameters in their risk weight calculations, and changes in the surrounding economic environment therefore need not have a large impact on risk weights.

Figure 5 shows a plot of average risk weight densities against average asset volatilities, with each point representing a bank. There seems to be a clear relationship between risk

Figure 4: The figure shows (left) the average asset volatility by year and (right) the average risk weight density (i.e. risk-weighted assets to total assets). In the right panel the average is both shown across banks (black) and for all banks, i.e. where the sum of risk-weighted assets is divided by the sum of total assets. The data are from S&P Global Market Intelligence.



weights and the estimated assets volatilities. It is evident that there are six banks which look somewhat like "outliers" in the sense that they have unusually high estimated asset volatilities relative to the other banks in the sample: Of these six banks, five are from Greece.

While asset volatilities appear to be related to risk weights, the same - as also found in the related literature - is not true for equity volatilities. This is illustrated in figure 6. The presence of a correlation between asset volatility and risk weights, but not equity volatility and risk risk weights is a consequence of banks with less risky assets being more leveraged at the same time.

Regressions of risk weights on asset volatilities confirm the association shown in figure 5. Table 2 shows the results of regressions of average risk weight densities on average asset volatilities as well as pooled regressions. Time fixed effects are included in the pooled regressions in order to capture level differences across years. As shown, estimated asset volatilities vary considerably from year to year, and much of this is likely due to other factors, e.g. changes in risk premia, than the risk associated with banks' assets.

The estimated effects of asset volatility differ depending on whether one looks at averages or pooled data, but it is clearly positive and significant in either case. The asset volatility explains more of the variation in risk weights when one looks at averages. This could be

Figure 5: The figure shows average risk weight density (x-axis) plotted against the average asset volatility (y-axis) for each bank in the sample. The data points are shown separately for banks using internal ["IRB"] models and for those using the standardized approach. The data are from S&P Global Market Intelligence.

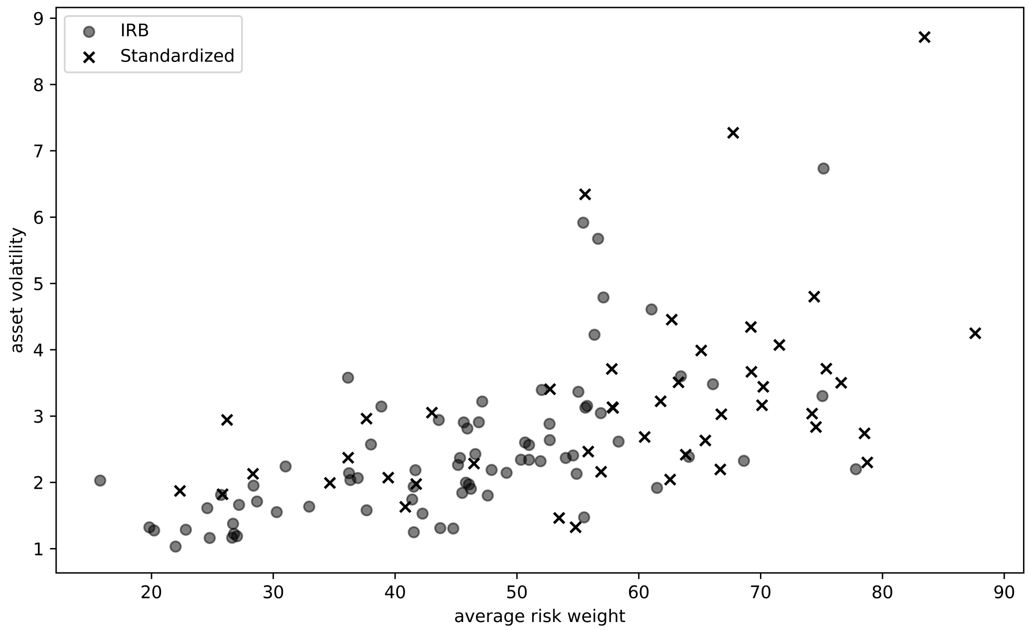
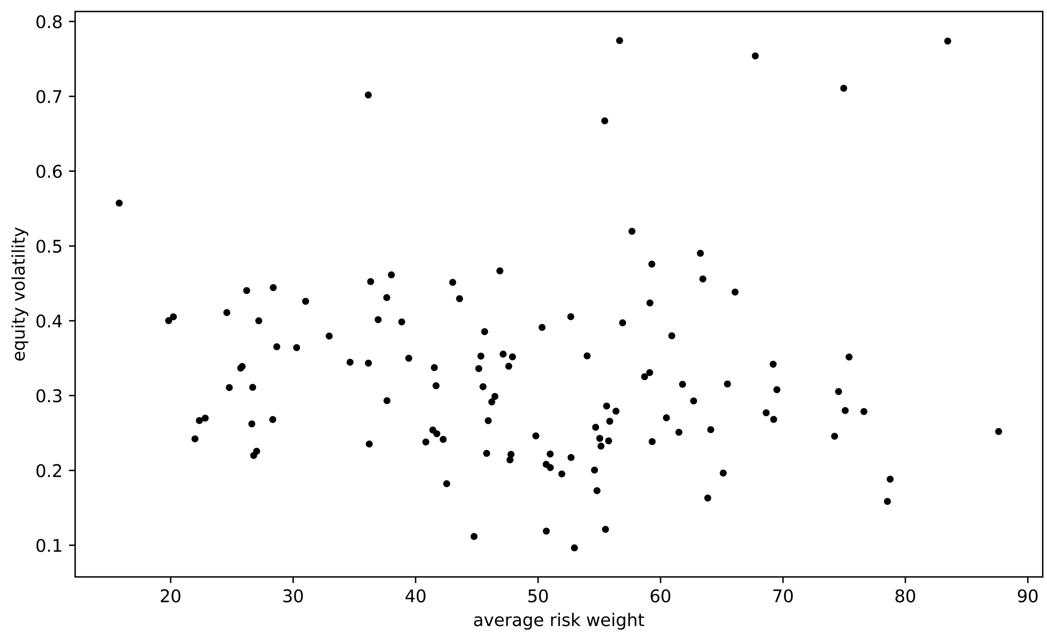


Table 2: This table shows the results of regressions of risk weight densities [i.e. risk-weighted assets to total assets] on asset volatilities. In the first regression, the data are time series averages for each bank, while in the second the data are pooled and time fixed effects are included. The data are from S&P Global Market Intelligence. Robust standard errors in parenthesis are clustered by country. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

	Regression of averages	Pooled regression
Asset volatility	7.471***	5.249***
	(0.956)	(0.280)
Time fixed effects	No	Yes
N	114	1018
Adj. R^2	0.347	0.282

Figure 6: The figure shows average risk weight density (x-axis) plotted against the average equity volatility (y-axis) for each bank in the sample. The data are from S&P Global Market Intelligence.



because risk weights are designed to capture risks over the cycle, and cyclical components are muted when looking at averages over more than a decade.

The results are not due to particular groups of banks such as the high risk Greek banks. In fact, the slope coefficient increases if the Greek banks are excluded from the analysis.

We can also separate the effects by whether banks use internal models or the standardized approach. Here, the results show that banks using internal models generally have lower risk weights while risk weights increase more with asset volatility than under the standardized approach, cf. table 3. However, the last effect is not statistically significant for regression of averages.

In the case where one only allows differences in intercepts (not reported in the table), the risk weights under the IRB approach are estimated to be about 6 percentage points lower than those under standardized approach.

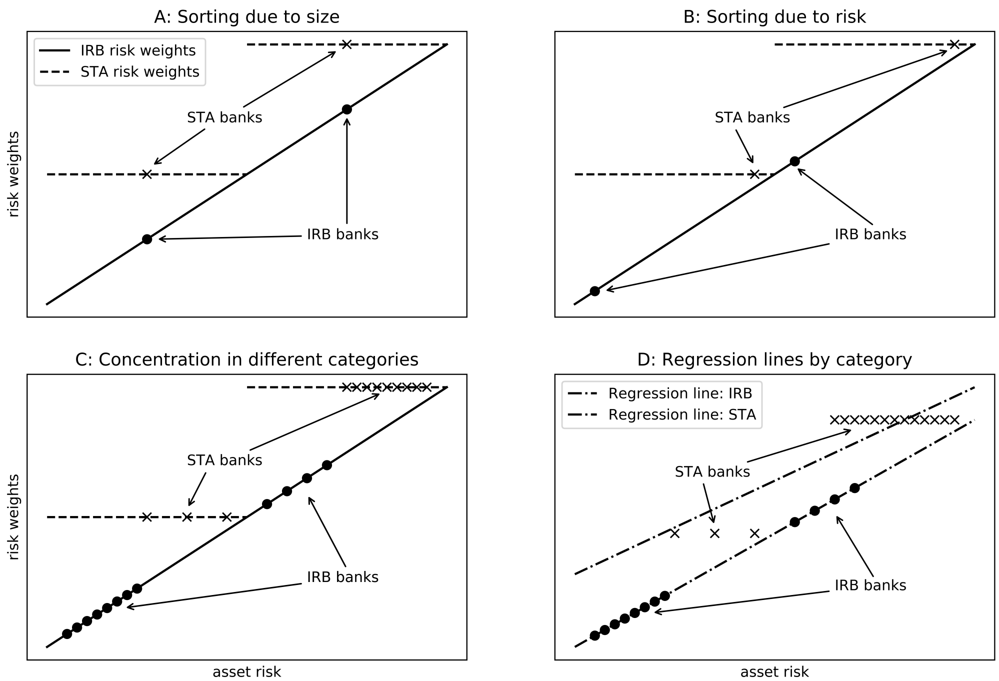
Table 3: This table shows the results of regressions of risk weight densities on asset volatilities, including an interaction term for the case of banks applying the standardized approach. The first regression is based on averages over time of risk weight densities and estimated asset volatilities. In that case banks are classified as either "IRB" or "Standardized" if they have applied that method for at least eight of the years in the sample and have used no other method during the sample period. The data are from S&P Global Market Intelligence. Robust standard errors in parenthesis are clustered by country. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

	Regression of averages	Pooled regression
Standardized approach	14.921**	14.910***
	(7.777)	(1.810)
Asset volatility	8.686***	5.844***
	(1.885)	(0.427)
Asset volatility x Standardized approach	-3.066*	-2.018***
	(2.427)	(0.540)
Time fixed effects	No	Yes
N	73	1007
Adj. R^2	0.476	0.358

The results are essentially as one should expect. If one looks at what predicts the choice to apply internal models, say by running a logistic regression, both bank size and asset volatility help predict the model approach. Larger banks tend to use internal models, whereas for smaller banks the fixed cost of building and maintaining such models may be prohibitive. Banks with safer assets (lower asset volatilities) are also more likely to use internal models.

I have tried to illustrate how these mechanisms might operate in figure 7. The figure shows a hypothetical example where risk weights under the standardized ["STA"] approach

Figure 7: The figure considers a hypothetical example in which there are two risk categories under the standardized ("STA") approach, with all assets having the same risk weight within these categories, while the relationship between asset risk and risk weights is assumed linear under the IRB approach. Panel A shows the case where sorting in approaches is not by risk, but some other factor such as size. Panel B shows the case where banks sort into approaches based on risk. Panel C illustrates the case where IRB banks also tend have lower risk assets and conversely for STA banks, while panel D shows how regression lines are expected to differ for IRB and STA banks given these mechanisms.



are non-granular and conservative. Concretely, they are split into two risk categories, with risk weights being identical within those categories. For banks using the IRB approach risk weights are assumed to be a linear function of risk.

Panel A shows the case where banks are sorted in groups for reasons other than risk. This could e.g. be due to size, with larger banks choosing the IRB approach because they can better afford the fixed cost of being an IRB bank. If one runs separate regressions of risk weights on asset volatility for IRB and STA banks in this case, the estimated slope coefficients would be identical, but the intercept term larger in the STA case.

In reality, there is also likely to be sorting because of risk. Banks with relatively safer assets within a risk category enjoy a greater advantage of switching to the IRB approach.

Conversely, banks using the standardized approach are likely to hold the more risky loans within a category. This is illustrated in panel B. In this case the regressions would again produce identical slope coefficients and different intercepts, although the difference would be smaller than in panel A.

There also seems to be a concentration of low risk banks in the IRB category and of higher risk banks in the STA category, as illustrated in panel C. For example, many of the lowest risk lenders are banks with large mortgage portfolios, and these generally use the IRB approach. If one takes this concentration effect into account, the regression slope also becomes flatter for banks using the standardized approach, which is consistent with what the data tells us.

One should expect a closer association between asset risk and risk weights for banks using internal models. This is also borne out in the data. In separate regressions for the IRB banks and those using the standardized approach, the asset volatility explains more of the variation in risk weight densities in the IRB case (R-squared: 0.373) than in the standardized case (R-squared: 0.233).[11]

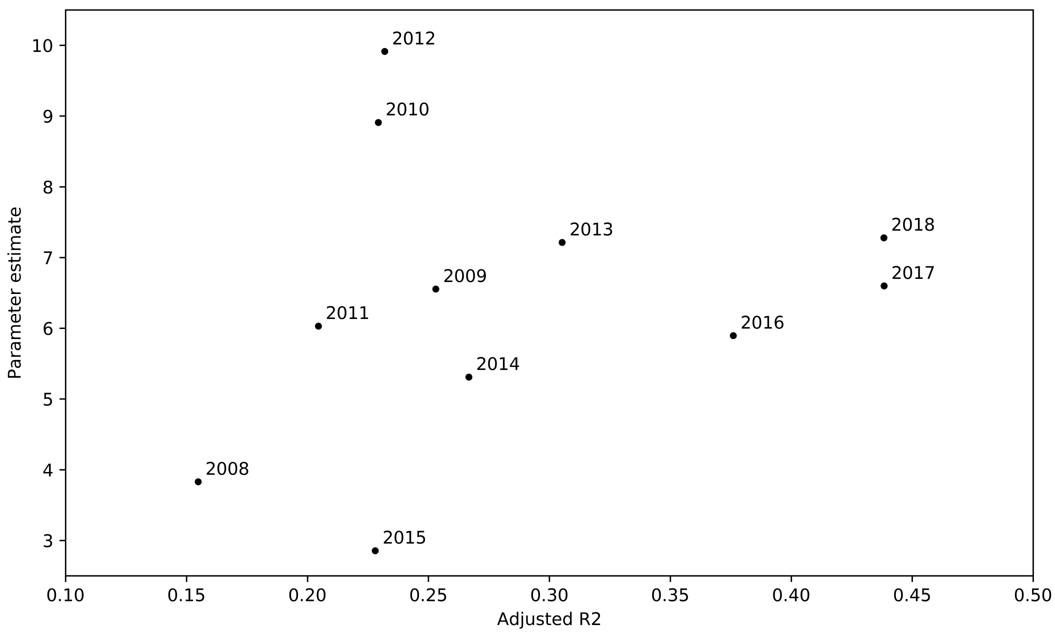
It might also be of interest to look at the results of regressions for each year in the sample. For example, over time banks have obtained more data and might therefore have become better at estimating the inputs in the risk weight formula - or perhaps at gaming the models. Figure 8 shows the parameter estimates from regressions of risk weight densities on estimated asset volatilities by year as well as the adjusted R-squared of these regressions in each year.

At least two observations stand out. First, the estimated effect of the asset volatility is larger in the years when the asset volatility accounts for more of the variation in the risk weights. Second, the years when the estimated effects are the smallest and when risk weights explain less of the variation in the data are also years when asset volatilities are generally the highest, e.g. 2008, 2011, and 2015 as shown in figure 4.

One interpretation of these facts might be that risk weights are less useful measures of risk when it really matters (i.e. when actual risks materialize). The zero risk weights assigned

[11] These figures are based on regressions of average values for each bank.

Figure 8: The figure is based on yearly regressions of risk weight densities on estimated asset volatilities over the period 2008-2018. It shows the adjusted R-squared from these regression (x-axis) and the parameter estimate of the asset volatility (y-axis) for each year in the sample. The data are from S&P Global Market Intelligence.



to sovereign bond holdings is a clear example of risk weights being imperfect measures of risk. This might help explain why asset volatility explains a smaller fraction of risk weight densities around the European sovereign debt crisis.

Another interesting observation is that asset volatility explains more of the variation in risk weights in the later years in the sample. The three years when the highest R-squared is recorded are the final three years (2016-2018). This observation is hard to reconcile with a "gaming" story in which banks gradually tweak their models so as to lower capital requirements.

However, one should also recognize that risk weights are limited in scope: They only reflect specific risks, mainly banks' credit risks, whereas asset volatilities inevitably also reflect a lot of other information such as general uncertainty, changes in risk premia, future earnings prospects, and so forth. One approach to dealing with this issue is to attempt to isolate the part of asset volatility which is related to credit risk. Table 4 shows the results of an attempt to do this. It includes the results of two-stage least squares estimations in which the part of asset volatility which is explained by credit losses (first stage) is used to explain risk weights (second stage). The estimated effects are somewhat larger in this case than in the earlier analysis.

Table 4: This table shows the results of two-stage least squares regressions. Models are included both for the case of averages for each bank in the sample and for the case of observations at the bank-year-level. In the first stage, the asset volatility is regressed on the bank's impairment rate (and time fixed effects in the pooled case), and the predicted asset volatilities are then used to explain the risk weight density in the second stage. The table shows the second stage results. The data are from S&P Global Market Intelligence. Robust standard errors in parenthesis are clustered by country. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

	Averages	Pooled regression
Asset volatility (1st stage)	9.109***	7.793***
	(1.404)	(0.462)
Time fixed effects	No	Yes
N	114	1007

As a final analysis, I look at whether current risk weights explain future credit losses. Risk weights are determined exactly with the aim of guarding against future (unexpected) losses so hopefully there is some cross-sectional relation between the two. To get a sense of how good or bad risk weights' explanatory power is, I run a simple "horse race" against a number of other variables. As dependent variables I look at the ratio of loan loss provisions to loans 1 year ahead and 3 years ahead. I then first run a baseline regression with only time fixed effects included then compare the R-squared of this regression with that of other regressions where the "horse race" variables are included one at a time. The results of this exercise are reported in table 5, both for the full sample and separately for the IRB banks and those using the standardized approach.

Table 5: This table shows the difference between R-squared in a regression of loan loss rates (either 1 or 3 years ahead) on the variable in question and time fixed effects and the R-squared of a regression with only time fixed effects included. The analysis is performed for the full sample of banks, IRB banks, and banks using the standardized approach ["STA"]. The data are from S&P Global Market Intelligence.

	Full sample		IRB banks		STA banks	
Variable	1 year ahead	3 years ahead	1 year ahead	3 years ahead	1 year ahead	3 years ahead
Risk weight density	.109	.134	.056	.061	.142	.209
Asset volatility	.172	.160	.230	.170	.110	.113
Asset volatility (Merton model)	.035	.054	.072	.077	.005	.011
Asset growth	.000	.000	.000	.001	.013	.012
Return on assets	.008	.009	.005	.008	.019	.001
Equity to assets	.005	.001	.001	.010	.003	.000
Log of assets	.003	.008	.001	.000	.000	.000
Total capital ratio	.066	.100	.087	.141	.050	.094

The calculated asset volatility explains more of future loan impairments than any of the other variables included in the horse race. Risk weights explain the second most, whereas variables such as asset growth, profitability (Return on assets), leverage, and size have no explanatory power. At odds with the notion of internal models being more "risk-sensitive" than the standardized approach, the risk weights under the standardized approach seem to do a better job of explaining future impairments than those under the IRB approach.

5. Conclusion

I have examined the relationship between risk weights and risk. The general conclusion is that risk weights do reflect risk, whether measured as banks' own projections of credit losses under stress, estimates of asset volatility, or actual future losses.

The paper thereby portrays risk weights in a kinder light than much of the related literature. This obviously should not be taken to mean that risk weights are without deficiencies. The risk weight formula used in the IRB approach is based on a stylized one-factor model, and there are obvious examples - such as the zero risk weights assigned to many sovereigns

- of imperfections under the standardized approach.

One can also argue about the merits of using internal models. The results are inconclusive as to whether the IRB approach is really more "risk sensitive" than the standardized approach. On the one hand, asset volatilities explain more of the variation in risk weights in the case of internal models. On the other hand, risk weights do a worse job of explaining the variation in future credit losses for the IRB banks than for those using the standardized approach. The results also show that, controlling for risk, banks which use internal models have lower risk weights. If one were to compare two banks with identical capital ratios, one using the standardized approach and the other using internal models, this would imply that, in general, the IRB bank is effectively more poorly capitalized. This has to be weighed against the benefits of internal models, such as potentially improved capital allocation, which are difficult to measure.

References

Acharya, V.V., Engle, R., Pierret, D., 2014. Testing macroprudential stress tests: The risk of regulatory risk weights. Journal of Monetary Economics 65, 36–53.

Angrist, J.D., Pischke, J.S., 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press .

Atkeson, A.G., Eisfeldt, A.L., Weill, P.O., 2017. Measuring the Financial Soundness of U.S. firms, 1926-2012. Research in Economics 71, 613–635.

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

Baule, R., Tallau, C., 2016. Revisiting Basel Risk Weights: Cross-sectional Risk Sensitivity and Cyclicality. Journal of Business Economics 86 (8), 905–931.

Behn, M., Haselmann, R., Vig, V., 2016. The limits of model-based regulation. ECB Working Paper Series No 1928.

Berg, T., Koziol, P., 2017. The limits of model-based regulation. Journal of Banking and Finance 78, 27–41.

Colliard, J.E., 2019. Strategic Selection of Risk Models and Bank Capital Regulation. Management Science 65 (6), 2445–2945.

Cucinelli, D., Di Battista, M.L., Marchese, M., Nieri, L., 2016. Credit risk in European banks: The bright side of the internal ratings based approach. ECB Working Paper Series No 1928.

Das, S., Sy, A.N.R., 2012. How Risky are Banks' Risk Weighted Assets? Evidence from the Financial Crisis. IMF Working Paper No 1236.

Ferri, G., Pesic, V., 2017. Bank Regulatory Arbitrage via Risk Weighted Assets Dispersion. Journal of Financial Stability 33 (C), 331–345.

Firestone, S., Rezende, M., 2016. Are banks' internal risk parameters consistent? Evidence from syndicated loans. Journal of Financial Services Research 50 (2), 211–242.

Mariathasan, M., Merrouche, O., 2018. The manipulation of Basel risk-weights. Journal of Financial Intermediation 39, 147–166.

Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.

Montes, C.P., Artigas, C.T., Cristófoli, M.E., San Segundo, N.L., 2018. The impact of the IRB approach on the risk weights of European banks. Journal of Financial Stability 39, 147–166.

Nagel, S., Purnanandam, A., 2019. Bank Risk Dynamics and Distance to Default. NBER Working paper no. w25807.

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

Vasicek, O.A., 1987. Probability of Loss on Loan Portfolio. KMV Corporation .

Vasicek, O.A., 1991. Limiting Loan Loss Probability Distribution. KMV Corporation .

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