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MODELING METHODOLOGY

Measuring and Managing Credit Earnings Volatility of a Loan Portfolio Under IFRS 9

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Abstract

IFRS 9 materially changes how institutions set aside loss allowance. With allowances flowing into earnings, the new rules can have dramatic effects on earnings volatility. In this paper, we propose general methodologies to measure and manage credit earnings volatility of a loan portfolio under IFRS 9. We walk through IFRS 9 rules and the different mechanisms that it interacts with which flow into earnings dynamics. We demonstrate that earnings will be impacted significantly by credit migration under IFRS 9. In addition, the increased sensitivity to migration will be further compounded by the impact of correlation and concentration. We propose a modeling framework that measures portfolio credit earnings volatility and discuss several metrics that can be used to better manage earnings risk.

Contents

1. Introduction

Earnings are one of the most important and scrutinized financial metrics. Equity price can be very sensitive to quarterly earnings announcements, and the price may exhibit large swings on reporting dates when realized earnings deviate from forecasts. Understandably, stakeholders generally prefer low earnings volatility, all else being equal. Managing that volatility requires a deep understanding of its drivers as well as strategies to help with its management.

Loan portfolios contribute a significant portion to a bank's earnings, in that, both the loan portfolio's accrued interest income and loss provision flow into a bank's net income account. Therefore, their performance impacts a bank's earnings volatility. Loan portfolio earnings dynamics are primarily driven by credit migration associated with the underlying borrowers, assuming interest rate risk is hedged away. Severe credit quality deterioration can result in increases in loss allowance or charge-off, which affects earnings negatively. Similarly, significant credit improvement with a risky asset can affect earnings positively. To highlight the dependence of portfolio earnings dynamics on credit, we refer to the earnings volatility generated by a standalone loan portfolio with hedged interest rate risk as credit earnings volatility.

The impact of credit migration on credit earnings volatility becomes more pronounced as the IFRS 9 loss recognition rule becomes effective. Under IFRS 9, financial institutions must set aside loss allowance for each instrument, measured as either one-year or lifetime expected loss. Allowance is updated on every reporting date to reflect the borrower's current credit condition. Since the borrower's credit quality, measured by a forward-looking Point-in-Time (PIT) probability of default (PD), tends to vary through time, the resulting portfolio loss allowance, and thus earnings, can exhibit substantial volatility. In addition, IFRS 9 can result in loss allowance displaying large spikes as an instrument migrates from "Stage 1" to "Stage 2," as allowance transitions from a one-year to a life-time measure. We will see that this Stage transitioning can have material impact on earnings volatility.

The discussion so far highlights the crucial need for a modeling framework that properly accounts for credit migration in order to measure accurately earnings risk. In addition, such a framework should accurately capture credit quality correlation across borrowers. The model should also recognize concentration and diversification, allowing for differentiation across, say deterioration in the Tech or Telecom sectors (as we saw in the early 2000's), from, say deterioration in the Financial, Retail, and Auto sectors (as we saw post-2008). Worth noting, earnings dynamics stemming from correlation are more pronounced when migration effects are prominent, as is the case with IFRS 9. This change is driven by loss allowance across instruments moving together in a more synchronized manner; a dynamic that is muted when allowances are more static. With granular models that capture these effects, we can examine the impact of IFRS 9 on earnings, how to model its impact in a portfolio setting, and how to construct meaningful risk metrics, which provide guidelines that allow for robust portfolio management practices.

We organize the remainder of this paper as follows:

- Section 2 discusses the impact of IFRS 9 on earnings and earnings volatility.
- Section 3 provides details on how earnings volatility can be measured ex ante.
- Section 4 relates earnings and earnings volatility to risk management and in decisions.
- Section 5 concludes.

2. Impact of IFRS 9 on Earnings

The earnings from a loan portfolio consists of interest income, change in the loss allowance, and net charge-off.[1] IFRS 9 affects the earnings of a loan portfolio through its impact on loss allowance. First, IFRS 9 requires an institution to recognize one-year expected credit loss for financial instruments as soon as the instrument is originated or purchased. It requires the institution to update loss allowance on reporting date accounting for the current credit environment, using a forward-looking PIT PD.[2] This requirement is very different from IFRS 9's predecessor, the IAS 39 standard, under which the loss allowance is less reflective of current credit condition, muting the effects of changes in the credit environment.[3]

Second, IFRS 9 introduces the concept of "Staging". When a borrower experiences a material deterioration in credit quality (but that continues to perform) and an associated credit exposure transitions from "Stage 1" to "Stage 2," loss allowance increases from one-year to life-time expected loss. Since the difference between one-year and lifetime expected loss can be very large, especially for longer dated instruments, loss allowance will exhibit a spike when the instrument transitions to "Stage 2." This is in contrast to IAS 39, which does not Stage assets in this way.

TABLE 1

Comparison of Earnings Dynamic Under IFRS 9 and IAS 39 — A Stylized Case Study

Time	Maturity (Years)	Rating	PIT PD	TTC PD	Stage	IAS 39 Loss Allowance (LA39)	IFRS 9 Loss Allowance (LA9)	Interest Income (II)	IAS 39 Earnings = II - ΔLA39	IFRS 9 Earnings = II - ΔLA9
0	5	Baa3	0.5%	0.5%	1	€25	€25	€0	€0	€0
Q1	4.75	Baa3	0.4%	0.5%	1	€25	€20	€25	€25	€30
Q2	4.5	Baa3	0.6%	0.5%	1	€25	€30	€25	€25	€15
Q3	4.25	Baa3	0.7%	0.5%	1	€25	€35	€25	€25	€20
Q4	4	Ba3	2%	2%	2	€100	€388	€25	€-50	€-328
…										

In general, IFRS 9 ties the dynamics of loss allowance more closely with the credit migration of the underlying borrower. The impact of IFRS 9 on loss allowance propagates to earnings as the change in loss allowance is directly recognized. Table 1 illustrates the difference between earnings for an individual instrument under IFRS 9 and IAS 39. In this example, we assume the instrument has a €10,000 face value, a five-year maturity, 50% LGD, and a 1% annual coupon rate with quarterly payments. We also assume that the loss allowance under IAS 39 equals to the one-year expected loss according to the Through-the-Cycle (TTC) PD implied by the rating of the instrument.[4] Under IAS 39, earnings generated by this instrument are constant in the first three quarters, because the credit rating and, hence, the TTC PD and loss allowance of the instrument does not change. Under IFRS 9 however, earnings fluctuate as the instrument's PIT PD changes. In the fourth quarter, the borrower experiences a severe downgrade, which lowers its credit rating from Baa3 to Ba3 and causes the instrument to be classified under "Stage 2," due to a substantial deterioration in credit. Consequently, the loss allowance under IFRS 9 increases significantly as the lifetime expected loss is recognized, resulting in large negative earnings for the quarter. While the earnings under IAS 39 is also negative during the quarter, its magnitude is much smaller than that under IFRS 9.

As illustrated by the example above, the volatility of earnings is higher under IFRS 9 than under IAS 39, as earnings are more closely tied to credit migration. As a side note, the question of whether IFRS 9 increases credit earnings volatility for a specific instrument depends on how we define the horizon up to which earnings are measured. For example, if we define horizon as the maturity date of an instrument, default is the only loss state, and earnings volatility will be independent of the loss recognition rule. In the end, accounting rules do not

[1] This paper focuses on the earnings for accrual loan book measured at amortized cost. However, similar analysis can be extended to FVOCI loan book as well.

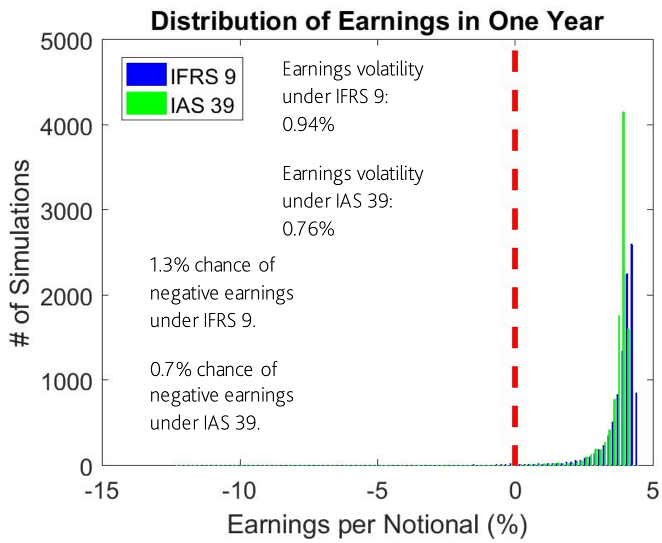
[2] Here we assume one uses forward-looking PIT PDs in implementing IFRS 9.

[3] As pointed out by the Basel Committee (2015) that the concern about the timeliness of loan provision under the IAS 39 standard was what gave rise to a series of sets of proposals that resulted in the publication of IFRS 9.

[4] Note that in practice, institutions are allowed to calculate IAS 39-compliant loss allowance based on Basel TTC PD and downturn LGD."

impact earnings if measured over an instrument's entire lifetime. Accounting rules only determine when and how these earnings are recognized. However, when the horizon is shorter than the maturity, and the impact of credit migration is taken into consideration, earnings volatility under different accounting standards will generally not result in the same dynamics in earnings. In practice, a loan portfolio consists of instruments with a variety of maturities that generally drive portfolio's earnings volatility affected by loss recognition rules. In general, earnings volatility of a loan portfolio is expected to be higher under IFRS 9 due to the "Staging" rule as well as the more frequent loss allowance update based on PIT PD. Indeed, in a recent survey on the impact of IFRS 9 conducted by EBA, 75% of the banks anticipate that IFRS 9 impairment requirements will increase volatility in profit or loss.[5]

Figure 1 Portfolio earnings distribution under IFRS 9 vs. IAS 39.



For illustration, Figure 1 compares the distribution of earnings for a sample portfolio of loans lent to European borrowers, under IFRS 9 and IAS 39.[6] In this example, we set the horizon to be one year, which is lower than the maturities of the instruments in the portfolio. As expected, the distribution of earnings under IFRS 9 has higher volatility and fatter tails than that under IAS 39. The observation that a portfolio is more likely to incur negative earnings under IFRS 9 may seem counterintuitive, as one would expect the higher initial requirement on loss allowance imposed by IFRS 9 would limit the downside of earnings. It is true that in a catastrophic event where all or almost all instruments in the portfolio default in a single period, the portfolio earnings during that period would be lower under the case where lower allowance were set under IAS 39compared with IFRS 9. However, the chance of such an event is negligible for a reasonably well-diversified portfolio. Instead, in a downturn economic scenario, we are more likely to observe downgrades from "Stage 1" to "Stage 2," causing the loss allowance to spike much higher under IFRS 9 than under IAS 39, resulting in lower earnings under IFRS 9.

[5] See "Report on Results from EBA Impact Assessment of IFRS 9," European Banking Authority, 2016.

[6] See Appendix A for the description of the sample portfolio.

3. Quantifying the Distribution of Earnings

The first step in quantifying earnings requires consideration of its components: $Interest\ Income_t$, change in $Loss\ Allowance$, and $Chargeoff_t$:[7]

$$Earnings_t = Interest\ Income_t - (Loss\ Allowance_t - Loss\ Allowance_0) - \text{Net}\ Chargeoff_t \quad (1)$$

In order to obtain the *distribution* of $Earnings_t$, the distribution of Interest Income;[8] Net charge-offs and Loss Allowance are needed; the value of each component along with the associated probability. The calculation of interest income, loss allowance, and charge-off due to defaults can be calculated in a relatively straightforward way when the credit state (i.e., PD and LGD) is known.[9] The challenging part is to estimate the probability of realizing each credit state, which requires the modeling of credit migration jointly across instruments in the portfolio. There are two important modeling elements that will be discussed in the following two sections: Section 3.1 reviews modeling dynamics of PD and LGD of individual instruments, and Section 3.2 reviews modeling correlation in credit quality across instruments.

3.1. Modeling Migration of PDs and LGD

The distribution of earnings are driven by dynamics in PD and LGD. For PD measures that are generally two broad classifications: through the cycle (TTC) and point in time (PIT). While there is no general accepted definition of either, for the purposes of the discussion in this paper, we will use a Moody's Rating to represent a TTC migration, and a Moody's Analytics EDF credit measure to represent a PIT measure. Table 2 and Table 3 provide examples of Ratings and EDF-based migration matrices, where each element denotes the transition probability from one rating or EDF (converted to equivalent rating) category to another in one year. The heavy weight on the diagonal of the ratings based transition matrix in Table 2 highlights the low likelihood of transitioning from the current credit state. Meanwhile the relatively high weights on the off diagonal of the EDF-based matrix seen in Table 3 is associated with a high likelihood of migrating up or down in credit quality.

TABLE 1

TTC Credit Migration Transition Matrix (%)

Initial Rating	Rating at End of One Year							
	Aaa	***Aa***	***A***	***Baa***	***Ba***	***B***	***Caa***	***Default***
Aaa	91.56	7.73	0.69	0.00	0.02	0.00	0.00	0.00
Aa	0.86	91.43	7.33	0.29	0.06	0.02	0.00	0.01
A	0.06	2.64	91.48	5.14	0.53	0.10	0.02	0.02
Baa	0.05	0.22	5.16	88.70	4.60	0.84	0.26	0.19
Ba	0.01	0.07	0.52	6.17	83.10	8.25	0.63	1.26
B	0.01	0.05	0.19	0.41	6.27	81.65	5.92	5.50
Caa	0.00	0.04	0.04	0.25	0.79	10.49	69.91	18.47

[7] Net charge-off is defined as the amount of loss due to default that is in excess of the loss allowance already booked.

[8] Note, since we assume no interest rate risk, the value of interest income is constant if an instrument does not default. However, the expected value of interest income recovered when the instrument defaults is less than the total interest income under no default.

[9] See "Implementation Guidance: IFRS 9 Financial Instruments," 2014.

TABLE 2

PIT Credit Migration Transition Matrix (%)

EDF Equivalent Rating	EDF Equivalent Rating at End of One Year							
	Aaa	**Aa**	**A**	**Baa**	**Ba**	**B**	**Caa**	**Default**
Aaa	65.50	20.10	8.50	3.90	1.20	0.80	0.10	0.00
Aa	25.53	36.57	25.80	9.20	2.17	0.50	0.10	0.07
A	4.10	18.03	41.03	27.17	7.77	1.63	0.17	0.07
Baa	0.43	2.87	19.17	46.27	24.87	5.47	0.67	0.30
Ba	0.10	0.17	2.33	21.27	49.77	22.97	2.70	0.60
B	0.00	0.00	0.20	2.00	18.50	55.70	21.40	2.17
Caa	0.00	0.00	0.00	0.30	1.80	20.60	63.60	13.60

Referencing Table 1, we can see the PIT measure produces much more dynamic allowances under IFRS 9 compared to the TTC measure used for IAS 39 allowance calculations. This finding is expected given the low probability of migrating across TTC categories compared with PIT.

Moving on to LGD, there are two broad approaches for accounting for volatility in LGD and the tendency for LGD to increase during deteriorating credit environments. With downturn-LGD, a single conservative term structure of LGD is used in allowance calculations and determining recovery. Alternatively, a model that explicitly accounts for the variance in LGD, as well as its correlated dynamics with PDs, is used in allowance calculations and determining recovery. This second approach allows for a more accurate representation of an instrument's earnings volatility. In particular, it accounts for the tendency of LGD to increase (decrease) when PD increases (decreases) properly accounting for the earnings volatility that this positive correlation produces. [10]

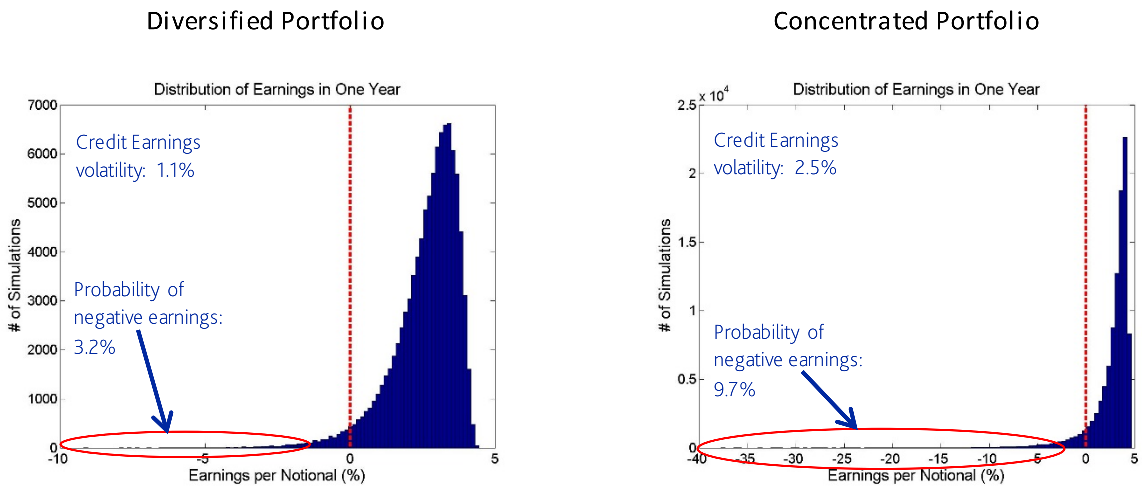
3.2. Modeling Credit Correlations

When describing the distribution of portfolio earnings, a characterization of how instrument's earnings co-vary is required. Figure 2 compares the distribution of earnings of two portfolios. In the "diversified portfolio," the correlation between instrument credit migration is lower than in the "concentrated portfolio." [11] We can see that the distribution of earnings differs significantly, with portfolio credit earnings volatility being significantly higher for the "concentrated portfolio." A sound correlation model is crucial for an accurate estimation of earnings volatility.

[10] For example, see Levy and Hu (2007) and Zhuang and Dwyer (2016).

[11] See Appendix A for the description of these two sample portfolios.

Figure 2 Credit earnings volatility and probability of negative earnings: diversified portfolio vs. concentrated portfolio.



While there are a number of approaches used for estimating correlations in various asset classes, credit correlations are particularly challenging given that credit is not typically traded and the dearth of publically available data. In addition, tractable representations of pairwise correlations are needed for credit portfolios that can frequently involve a high dimensionality of instruments and borrowers.

Factor models such as GCorr have proven to work well in describing credit correlations.[12] These factor models frequently determine the correlation structure of default probabilities through a description of asset correlations; the correlation of the borrower's underlying assets. They can also describe the correlation of LGD (or recovery), leveraging correlated factors.

The benefits of leveraging a factor structure such as GCorr include an ability to differentiate across counter parties' sensitivity to systematic factors, as well as differentiating across counter parties' sensitivity to industry and country factors. GCorr has the added benefits of broad asset class coverage as well as integrated linkages to macroeconomic variables.

Ultimately, the migration and correlation models allow mapping portfolio earnings dynamics, as well as providing a sense for the pockets of concentration and potential areas of diversification, helping guide strategic business decisions.

[12] See "Modeling Credit Portfolios," 2015, for a detailed description of the GCorr factor model.

4. Earnings and Business Decisions

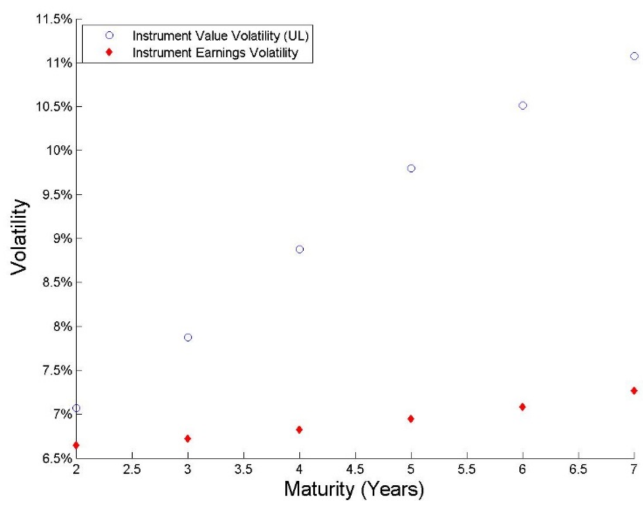
With a framework that recognizes loss accounting rules, migration, and correlation dynamics, we can calculate several risk metrics that provide insight to managing earnings dynamics and support strategic decisions. In the subsections below, we discuss the definition and application of credit earnings volatility (CEVol), credit earnings at risk (CEaR), credit earnings risk contribution (CERC), and credit earnings tail risk contribution (CETRC). These measures should supplement traditional risk measures such as Economic Capital and RORAC, as they provide an additional lens in assessing the value of various strategies. Earnings measures provide an assessment of portfolio risk from an accounting perspective rather than from a conventional economic perspective. Ultimately, risk managers may consider consolidating the credit earnings volatility measures with traditional measures to obtain a composite view of risk.

4.1. Credit Earnings Volatility

Credit earnings volatility refers to the standard deviation of earnings over a horizon (usually one-year) assuming deterministic interest rate. In conventional risk management, a similar concept to credit earnings volatility is the standard deviation of the instrument value or loss at horizon, which is also referred to as Unexpected Loss (UL). At the instrument level, the two concepts are similar in the sense that both measure risk of credit instruments caused by credit migration. There are important differences though. For non-defaulted asset, credit earnings volatility stems from the uncertainty in loss allowance at horizon. For "Stage 1" instruments, the uncertainty in loss allowance is limited to the variation in one-year expected loss. By contrast, UL measures the uncertainty in instrument value, which, regardless of the staging, reflects the change in an instrument's value, where value accounts for the discounted expected cash flows over the instrument's life.

Figure 3 depicts the difference between the credit earnings volatility and UL, where we examine the relationship between maturity and credit earnings volatility and UL for a "Stage 1" instrument over a one-year horizon. We find that an instrument's UL grows substantially as its maturity increases. This is expected as longer dated instruments are more sensitive to changes in credit quality. By contrast, the instrument credit earnings volatility remains relatively flat as the maturity increases, because the main driver of credit earnings volatility — the loss allowance at horizon — measures one-year expected loss regardless of the maturity of a "Stage 1" instrument under the IFRS 9 rule. It is noteworthy that the credit earnings volatility still has a positive albeit small upward slope as a function of maturity. This trait follows because the instrument may migrate to "Stage 2" at horizon and, thus, has a probability of allowance being measured under lifetime expected loss. It is interesting to observe that IFRS 9 does make longer-dated assets appear more attractive than they would under an economic lens; especially those that are far from migrating to "Stage 2."

Figure 3 Instrument credit earnings volatility vs. value volatility (UL).



4.2. Credit Earnings at Risk

As illustrated in Figure 1, the distribution of portfolio earnings is generally heavy tailed and skewed with a high probably of realizing negative values; credit earnings volatility alone does not provide a comprehensive description of the portfolio risk. For institutions interested in knowing the performance of the portfolio under a stressed scenario, it is important to understand the dynamics of earnings in the tail of the distribution. An intuitive and common way to measure the tail risk is to compute the value of portfolio earnings at a certain percentile, say 10bps. Credit Earnings at Risk (CEaR) represents portfolio earnings (or loss) when realizing, say, a 10bp event. The concept is similar to that of Value at Risk (VaR), and, in practice, CEaR can help guide risk managers in assessing the capital buffer needed to limit the likelihood of insufficient capital.

4.3. Credit Earnings Risk Contribution and Tail Risk Contribution

Measures such as credit earnings volatility and CEaR are portfolio-level risk metrics. In this sub-section, we introduce risk measures that describe the extent to which an instrument (or sub-portfolio) contributes to the overall portfolio risk. To account for the concentration and diversification effect, the portfolio-referent measures capture correlation between the earnings of the underlying instrument or sub-portfolio and those of the overall portfolio. Credit Earnings Risk Contribution (CERC) is defined as the marginal contribution of an instrument to the portfolio earnings volatility:

$$CERC_i = \frac{\partial CEVol_P}{\partial V_i} \quad (2)$$

Where V_i is the exposure to instrument i in the current portfolio. Note, we can represent ERC as the covariance between instrument and portfolio credit earnings divided by portfolio credit earnings volatility: [13]

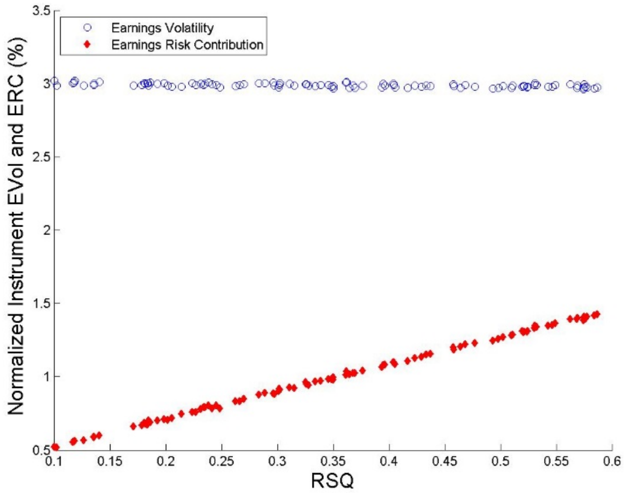
$$CERC_i = \frac{Cov(Earnings_i, Earnings_P)}{V_i \times CEVol_P} \quad (3)$$

Equation (3) clearly demonstrate that ERC is a portfolio-referent risk metric, and it is larger for an instrument whose earnings are more correlated with portfolio earnings.

Figure 4 illustrates how dynamics in concentration and diversification are captured in CERC for a sample portfolio. The portfolio has 100 loans with identical risk characteristics except for their correlation with systematic factors. As discussed in Section 3.2, in the GCorr model an instrument's correlation with the systematic factors is captured through its RSQ parameter; as RSQ increases, the instrument's earnings correlation with systematic drivers increase. In other words, everything else equal, the higher the value of RSQ, the more correlated an instrument is with the rest of the portfolio, and the more concentration risk is generated through the instrument. Indeed, Figure 4 shows that instrument ERC increases as RSQ increases, while stand-alone instrument credit earnings volatility remains constant. Notice, the CERC level is always lower than credit earnings volatility. This follows from each individual instrument adding diversification benefits to the portfolio; this diversification benefit is properly reflected by credit earnings risk contribution but not by credit earnings volatility.

[13] See Appendix C for the derivation of the CERC.

Figure 4 Instrument-normalized CERC and RC vs. RSQ.



CERC has several business friendly applications, including capital allocation, risk-based limits, and RORAC-style strategy investment/origination rules that maximize expected earnings given the level of earnings risk. Institutions can rank order instruments according to Credit Earnings Sharpe Ratio (CESR), defined as

$$CESR_i = \frac{E(Earnings_i)}{V_i \times ERC_i} \tag{4}$$

A straightforward rule of thumb for business decisions is to invest in instruments with ESR higher than the portfolio ESR and reduce holdings of instruments with lower CESR:

$$CESR_i > CESR_P = \frac{E(Earnings_i)}{EVol_P} \tag{5}$$

Such a strategy maximizes the ratio between expected earnings and earnings volatility for the overall portfolio.

As discussed in Section 4.2, some stakeholders may prefer to use a tail risk measure. One portfolio-referent measure of earnings tail risk is Credit Earnings Tail Risk Contribution (CETRC), which measures the instrument's contribution to the risk of a level of loss, potentially an extreme (e.g., 10bp event). Formally, CETRC is defined as the change in portfolio CEaR due to a marginal increase in an instrument's position:

$$CETRC_i = \frac{\partial CEaR_P}{\partial V_i} \tag{6}$$

Note, Equation (6) can expressed as:[14]

$$CETRC_i = \frac{1}{\mathrm{V_i}} E(Earnings_i | Earnings_P = CEaR_P) \tag{7}$$

Equation (7) shows that CETRC can be represented as the expected earnings conditional on portfolio earnings equaling CEaR. For practical consideration, CETRC is generalized to measure the expected earnings conditional on portfolio earnings falling within a range ($Earnings_P^{Lower}$ to $Earnings_P^{Upper}$):

$$ETRC_i = \frac{1}{\mathrm{V_i}} E\left(Earnings_i \middle| Earnings_P^{Lower} \leq Earnings_P \leq Earnings_P^{Upper}\right) \tag{8}$$

Similar to CESR, a risk-return tradeoff measure based on CETRC can be defined as:

[14] See Appendix C for derivation.

$$CEVR_i = \frac{E(Earnings_i)}{V_i \times CETRC_i} \tag{9}$$

A business decision-making rule similar to the one with CESR also exists to ensure the portfolio return to tail risk ratio is maximized:

$$CEVR_i > CEVR_P = \frac{E(Earnings_P)}{\sum_{j=1}^{N} V_j \times CETRC_j} \tag{10}$$

Note, the choice between CESR and CEVR depends on an institution's subjective view of risk. If the institution perceives risk as the general volatility of earnings generated by a portfolio, CESR is the ideal choice. On the other hand, if the institution regards risk as the probability of extreme loss or capital breach induced by negative earnings, CEVR is likely a better choice.

Both CERC and CETRC only account for the risk associated with earnings. In addition to earnings risk, institutions must also manage the risk associated with the economic value of a loan portfolio while facing regulatory capital requirement constraints. One approach brings together economic risks, earnings, and accounting effects, as well as regulatory requirements in strategic decision-making rules through a Composite Capital Measure (CCM) and related CCM RORAC measure introduced in Levy, Xuan, and Xu (2016).

5. Summary

IFRS 9 creates material changes in the dynamics of earnings associated with loan portfolios, with portfolio earnings likely becoming more dependent on credit migration than under IAS 39. As a result, correlation effects will be more pronounced, and the credit earnings volatility of many loan portfolios will increase. The impact of IFRS 9 signifies the importance of credit risk management of earnings. We link loss recognition rules with sound modeling of credit migration and correlations. We then leverage well established and understood measures of risk allocation and strategic decision rules to design a framework for institution to measure and manage uncertainty in portfolio earnings.

Appendix A – Description of the Sample Portfolio Used in Figure 1

The sample portfolio in Figure 1 is synthetically constructed as a representative loan portfolio held by an EU bank. The portfolio contains one fixed rate term loan lent to each of the 4734 public firms in EU countries as of Q1 2014. The notional amount of these term loans are approximately proportional to underlying obligors' total debt liabilities. The maturity of each loan is randomly generated with a uniform distribution from 1–7 years. The fixed coupon rate of each loans is set to be par yield. The summary statistics and country and industry concentration are reported in Table 4 and Table 5.

TABLE 3
Summary Statistics of the Sample Portfolio in Figure 1

Total Number of Obligors	4,734
Total Notional Amount	€140 Bn
Average PD (weighted by notional)	0.45%
Average LGD (weighted by notional)	59%
Average RSQ (weighted by notional)	0.41
Average Maturity (weighted by notional)	4.2
Average Annual Coupon (weighted by notional)	4%
Percentage of Stage 2 Assets (by counts)	21%

TABLE 4
Country and Industry Concentration of the Sample Portfolio in Figure 1

Country	Exposure Weight	Industry Name	Exposure Weight
UK	29%	banks and S&Ls	21%
France	20%	utilities, electric	8%
Germany	18%	automotive	8%
Italy	8%	security brokers & dealers	6%
Spain	7%	business services	5%
Netherland	5%	telephone	5%
Sweden	3%	investment management	4%
Belgium	2%	insurance - life	4%
Austria	1%	oil refining	4%
Denmark	1%	construction	3%
Rest	6%	Rest	34%

Appendix B – Description of Sample Portfolios Used in Figure 2

The "Diversified" and "Concentrated" portfolios are synthetic loan portfolios of 100 term loans. All risk characteristics except RSQ of all loans in the "Diversified" portfolio are randomly generated and copied to the loans in the "Concentrated" portfolio. RSQ — the variable that measures how much the credit migration of each obligor is correlated with systemic factors, is set as 0.1 for all loans in the "Diversified" portfolio, but set as 0.4 for all loans in the "Concentrated" portfolio.

Appendix C – Derivation of Formulas

Derivation of Equation (3):

First, note that portfolio credit earnings volatility has the following form:

$$CEVol_P = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} Cov(Earnings_i, Earnings_j)} = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} V_i \times V_j \times Cov(\overline{\overline{Earnings_i}}, \overline{\overline{Earnings_j}})} \quad (11)$$

Where $\overline{\overline{Earnings_i}}$ denotes the earnings per unit of holding amount for instrument i.

Plug-in Equation (11) into Equation (2), we have

$$CERC_k = \frac{\partial \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} Cov(V_i \times \overline{\overline{Earnings_i}}, V_j \times \overline{\overline{Earnings_j}})}}{\partial V_i} = \frac{\sum_{j=1}^{N} V_j \times Cov(\overline{\overline{Earnings_k}}, \overline{\overline{Earnings_j}})}{\sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} V_i \times V_j \times Cov(\overline{\overline{Earnings_i}}, \overline{\overline{Earnings_j}})}} \quad (12)$$

Multiply both the numerator and denominator in Equation (12) by V_k, we have

$$CERC_k = \frac{\sum_{j=1}^{N} Cov(V_k \times \overline{\overline{Earnings_k}}, V_j \times \overline{\overline{Earnings_j}})}{V_k \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} V_i \times V_j \times Cov(\overline{\overline{Earnings_i}}, \overline{\overline{Earnings_j}})}} = \frac{Cov(Earnings_k, Earnings_P)}{V_k \times \sqrt{\mathrm{EVol_P}}} \quad (13)$$

□

Derivation of Equation (7):

First note that the sum of instrument expected earnings conditional on the fact portfolio earnings is by construction exactly CEaR:

$$E\left(\sum_{j=1}^{N} V_j \times \overline{\overline{Earnings_j}} \,|\, Earnings_P = EaR_P\right) = CEaR_P \quad (14)$$

Replacing the value of EaR_P in Equation (6) by the left hand side in Equation (14), we have

$$CETRC_i = \frac{\partial E\left(\sum_{j=1}^{N} V_j \times \overline{\overline{Earnings_j}} \,|\, Earnings_P = CEaR_P\right)}{\partial V_i} \quad (15)$$

Because both the conditional expectation and the summation in Equation (15) are linear operators, the partial derivative operation can be carried out directly inside the summation:

$$CETRC_i = E\left(\sum_{j=1}^{N} \frac{\partial\left(V_j \times \overline{\overline{Earnings_j}}\right)}{\partial V_i} | Earnings_P = CEaR_P\right) \quad (16)$$

Since the partial derivative is zero for all $j \neq i$ and is $\overline{\overline{Earnings_i}}$ for $j = i$, we have

$$CETRC_i = E\left(\overline{\overline{Earnings_i}} | Earnings_P = CEaR_P\right) = \frac{1}{V_i} E\left(Earnings_i | Earnings_P = CEaR_P\right) \quad (17)$$

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