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Credit Market Research
Financial Institutions
Special Report

Basel II Correlation Values

An Empirical Analysis of EL, UL and the IRB Model

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Related Research

- *Criteria Report, "How Much Credit in Credit Risk Models?," dated May 8, 2007.*
- *Special Report, "Basel II: Bottom-Line Impact on Securitization Markets," dated Sept. 12, 2005.*
- *Special Report, "Demystifying Basel II: A Closer Look at the IRB Measures and Disclosure Framework," dated Aug. 25, 2004.*

Introduction

This report provides an empirical study of the Basel II asset value correlation assumptions for the internal ratings-based (IRB) approach. By statistically analyzing empirical loss data within the context of the IRB modeling framework, Fitch Ratings is able to derive correlation estimates across a range of asset types that are consistent with the long-run historical performance and risk profile of these assets. The methodology enables financial institutions analysts to assess the Basel II correlation assumptions and, in turn, IRB capital levels for particular portfolios. Important findings are as follows.

- Across asset classes, the Basel II asset value correlation assumptions are generally more conservative (i.e., higher) than the correlations derived in this empirical study. Fitch finds that this conservatism helps to address the global scope of Basel II and the need to accommodate, for example, differences across banks in risk factor sensitivities, single-obligor concentration risk and model risk (e.g., uncertainty and variability in banks' internal default and loss severity estimates).
- An important consideration in evaluating Basel II ratios of financial institutions, however, is that defaults tend to cluster, correlations increase, and loss rates exceed historical means during periods of financial market stress. Thus, while the Basel II assumptions appear conservative relative to empirically derived correlations during "normal" market conditions, it is unclear whether the Basel II assumptions sufficiently capture correlation "jumps" during market crises.
- Additionally, it is important to keep in mind that the Basel II correlations are static values describing the behavior of dynamic assets whose future loss experience is dependent on financial product innovation, changes in risk factors (e.g., underwriting practices), and structural shifts in financial markets. For example, the delinquency rates currently materializing on recent vintages of subprime residential mortgages reflect sensitivities to risk factors (e.g., home price declines, the rapid growth of high-risk "affordability" features, deterioration in mortgage underwriting practices, higher loan-to-value ratios, and fraud misrepresentations within the origination process) that are causing differences in performance relative to the longer-run history for this asset class. Anecdotal evidence suggests that correlations for these more recent vintages likely will exceed the correlations derived from analyzing longer-run empirical loss data for mortgages, exemplifying the dynamic nature of correlations.
- Fitch views stress testing, particularly scenarios based on a higher correlation environment, as critical in evaluating the rigor and relevance of the Basel II capital charges in different contexts. Additionally, Fitch views empirically based analysis as an important ongoing exercise for broadly assessing the appropriateness of the Basel II correlations across bank portfolios globally. Empirical analysis is particularly important for evaluating Basel II capital charges on portfolios exposed to geographic and other systematic risk factors, and to undiversified idiosyncratic risk not fully reflected by the Basel II calibration.
- In comparing correlation values across asset classes, the Basel II correlation assumptions appear to be appropriate on a relative or ordinal basis. More specifically, the asset classes with the highest Basel II correlation assumptions (i.e.,

commercial mortgages and corporates) also generated the highest empirically derived correlation values in the study.

- Contrary to Basel II assumptions for certain asset classes, there generally does not appear to be a uniform statistical relationship between asset correlations and probability of default (PD). For some asset classes, Basel II assumes that correlations decrease as a function of PD (i.e., that the correlation values for higher PD or lower-quality obligors is lower). The empirically derived correlations suggest that for certain asset classes, the correlations are in fact higher for higher PD borrowers—directionally opposite to the Basel II assumptions.
- Empirically derived correlations vary geographically, suggesting that the Basel II assumption of applying the same correlation values globally might not appropriately differentiate the relative risk profiles of banks in different regions. For example, the empirically derived correlations based on US versus UK bank data differ across asset classes. These differences are important to bear in mind when making international comparisons of banks' IRB ratios, but more importantly might pose prudential concerns for credit portfolios exposed to particularly volatile geographic markets.
- The use of different distributional assumptions (i.e., beta, Weibull, lognormal and Vasicek[a] distributions) does not alter the results in a meaningful way and provides generally comparable correlation estimates.

It is important to note that the empirically derived asset correlations analyzed within this study apply to portfolios of loans (e.g., residential mortgages, commercial mortgages, credit cards, auto loans, etc.) and are estimated based on the formulas and assumptions underlying Basel II. This study uses historical structured finance data to help evaluate the Basel II correlation assumptions, but does not imply that Fitch views the resulting correlation estimates as directly comparable with a structured finance modeling and ratings perspective. Additionally, these empirically derived correlations should not be extrapolated to the analysis of correlations within re-securitizations (e.g., collateralized debt obligations backed by asset-backed securities).

Asset Correlation, Expected Loss and Unexpected Loss under Basel II

The IRB approach is the cornerstone of the new Basel II risk-based capital framework for credit risk. The IRB approach harnesses quantitative estimates of obligor-level risk (e.g., the probability of default or PD and loss given default [LGD]) and is grounded in well established concepts from modern portfolio-based risk management. Basel II thus provides a more meaningful and sophisticated capital framework than the 1988 Accord (or Basel I). While clearly an important advance in measuring and managing risk-based regulatory capital, the IRB framework embeds several simplifying assumptions that are important to understand when calculating and analyzing IRB capital charges.

Perhaps the most notable IRB assumption is the level of the correlation parameter. Regulators have calibrated and set predetermined values for the correlation parameter within each of the IRB formulas, which are broadly segmented by asset class definitions specified under Basel II (e.g., corporates, commercial mortgages, residential mortgages,

[a] The so-called Vasicek distribution underlies the Basel II framework. A Vasicek loss distribution has the density $f(x;p,\rho)=\sqrt{\frac{1-\rho}{\rho}}\exp\left(\frac{-1}{2\rho}\left(\sqrt{1-\rho}\cdot N^{-1}(x)-N^{-1}(p)\right)^2+\frac{1}{2}\left(N^{-1}(x)\right)^2\right)$ where ρ is the asset correlation, x is an evaluation parameter ($0\le x\le 1$) and p is the unconditional default probability.

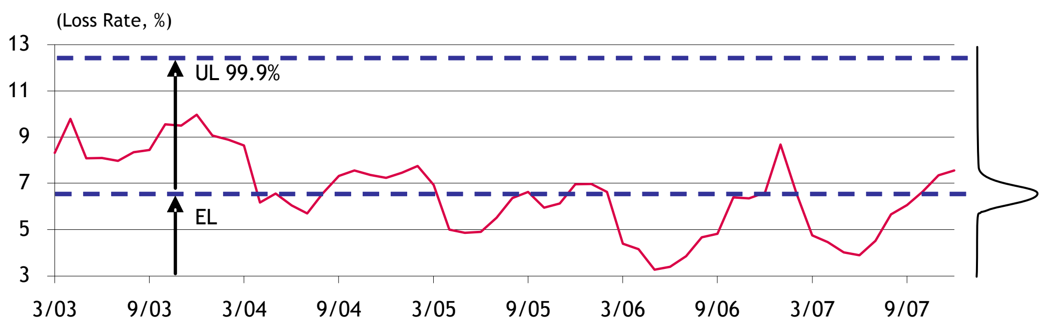
credit cards and consumer lending). The regulatory-specified levels of the correlation parameters are the most important differentiator across the IRB formulas and a critical driver of the amount of Basel II capital generated across the different asset classes.

The IRB approach is based on credit risk modeling concepts that are broadly consistent with credit economic capital models used increasingly by financial institutions to measure portfolio-level risk and to manage and allocate capital across the enterprise. The IRB approach, however, is based on an asymptotic single-risk factor calculation methodology that allows easy analytical solutions, rather than a full-blown multi-factor model typical of internal bank credit economic capital systems (for an intuitive explanation of the IRB framework and its conceptual underpinnings, see Fitch's Special Report, "Demystifying Basel II: A Closer Look at the IRB Measures and Disclosure Framework," published Aug. 25, 2004).

At its essence, the IRB approach is a model for generating a distribution of portfolio credit losses, which can be decomposed into expected loss (EL) and unexpected loss (UL) components. The IRB capital charges are designed to cover UL, with the EL component covered by loan-loss reserves.

Conceptually, EL is akin to the mean loss rate of a portfolio and represents the loss that a bank can reasonably anticipate will occur over a given time horizon. EL is simply an aggregated measure of the PD of each obligor in the portfolio multiplied by its LGD,[b] since the bank can expect to lose an amount equivalent to the likelihood of each obligor defaulting adjusted by the proportion of the exposure that will not be recovered upon that default.

Loss Rate, Expected Loss, and Unexpected Loss for US Auto Loans



Note: The EL corresponds to the mean loss rate within the data sample, while the UL is a high quantile measure of variability in losses relative to the mean. The EL and UL estimates represent different points within the credit Loss distribution to the right of the loss rate graph.
Source: Fitch Ratings, Basel Committee on Banking Supervision.

Of course, in reality, more obligors in a portfolio might default than is expected, particularly if the financial performance of these obligors is sensitive to common or similar risk factors. This variability in default rates could, all else being equal, drive portfolio loss rates higher than expected or average levels. Similarly, the portfolio loss rate could also exceed expectations if the portfolio is not well diversified and contains a

[b] Note that the LGD variable in the IRB calculations is a "downturn" LGD rather than an average LGD. The downturn LGD is intended to reflect cyclical variability in loss severities (i.e., positive correlation of default rates and loss severities), with higher severities expected during market downturns.

Basel II Rationale for not Permitting Bank-Derived Correlation Estimates

There are several reasons for why Basel II regulators have developed the IRB approach rather than permitting the use of "full-blown" internal portfolio credit risk models for setting minimum regulatory capital levels.

- Basel II regulators do not have full comfort with regulatory capital being a function of bank-derived correlation parameters, which is an area of evolving empirical and theoretical research. Additionally, regulators are already grappling with potential variability in bank estimates of PD and LGD, with different banks sometimes generating markedly different default risk estimates on the same underlying obligors.
- By "hardwiring" the charges formulaically and fixing correlation values at a predetermined level, the IRB framework provides bank supervisors with a more consistent and tractable benchmark for assessing capital adequacy across banks. Allowing banks to measure regulatory capital based on their own correlation estimates would introduce an influential source of measurement variability, making it difficult for supervisors (and market participants) to systematically compare risk-based capital ratios across banks.
- Adjusting the correlation values is a policy lever for regulators to achieve desired capital outcomes. For example, by increasing correlation assumptions, regulators are able to increase overall Basel II capital requirements.

few particularly sizable exposures to obligors that happen to default. This variability in loss rates relative to the mean loss rates, driven either by sensitivities to common systematic risk factors or by concentrated single-obligor risk exposures, is UL. The IRB formulas are designed to generate an estimate of UL, equivalent to the minimum amount of Basel II capital required on a particular asset.

The chart on page 3 illustrates the concepts of UL and EL, showing a time series of loss rates for an index of US auto loans to highlight some salient features of the loss distribution.

How Well Do the Basel II Correlation Assumptions Reflect Actual Loss Experience?

The question arises as to how well the correlation values that have been calibrated by Basel regulators reflect the risk profile and actual loss experience of credit portfolios. In other words, are the Basel correlation assumptions higher than actual experience, which would suggest relative conservatism in capital levels? Or, are the Basel correlation assumptions relatively low, which might indicate relative laxity in capital levels? Addressing these questions is important, given the strong impact of correlations on IRB capital calculations and, in turn, on the adequacy of bank capital levels as measured by the new framework (not to mention the potential financial market impact in the form of regulatory incentives to either increase or mitigate credit exposure to certain asset classes).

The challenge is to identify and to apply an appropriate methodology for deriving empirically based asset correlations in the context of Basel II. For this study, asset correlation values are derived by analyzing historical loss data (rather than asset return or default data) for the respective Basel II asset classes.[c] The basic premise is that correlation is manifested in realized variability or volatility in portfolio losses over time. Portfolios comprised of assets that are more highly correlated will generally experience higher volatility of losses (UL) relative to the mean loss rate (EL). Likewise, portfolios comprised of less correlated assets will experience lower volatility in loss rates relative to the mean loss rate.

This study statistically analyzes both the mean and volatility of empirical loss rate data to enable the estimation of EL and UL, which in turn can be used to derive the correlation value that would generate that same level of UL within the IRB formulas.

Methodology: Calibration of IRB Correlation Values

The initial step in empirically deriving IRB correlations is to source a robust time series of pooled loss observations for each Basel II asset class being studied. Important attributes of such time series are frequency of observations, size of data set (i.e., having more obligors or exposures in the pool is preferable), and consistency with Basel II asset class definitions. It is also important that the data set capture a period of market stress or relative underperformance for the asset class, since empirical analysis focused solely on benign market conditions would understate correlations.

This study relies on three primary sources of data: charge-off rates published by the Federal Reserve for bank-held exposures, loss rates for UK banks published by the Bank of England, and aggregated loss rates on the underlying collateral assets within Fitch-rated US structured finance transactions. Note, however, that the use of structured finance data for performing this Basel II research does not imply that Fitch views the resulting correlation estimates as directly comparable with a structured finance modeling and ratings perspective.

The Federal Reserve and Bank of England data sets have the advantage of representing exposures held on bank balance sheets. Fitch-rated structured finance data enable richer analysis of, for example, differences in borrower credit quality (e.g., prime versus subprime) as well as by vintage, which is important given that retail asset portfolios are typically managed in the context of actuarially consistent seasoning patterns in default rates from origination through to maturity.

The next step is simply to calculate the mean and standard deviations of the loss rates across the given time series for the particular asset class. The result is a mean and standard deviation statistic corresponding to each data set. These two statistics are essential to deriving correlation values from the IRB formulas.[d]

Deriving IRB correlations involves further statistical analysis of the mean and standard deviation of loss rates. The mean loss rate is assumed to be analogous to EL (note that EL in this context differs from the EL concept typically used within the structured finance ratings process, which represents a forward-looking measure of projected "base case" losses on a given portfolio). For consistency with the IRB formulas, this EL estimate (i.e., the mean loss rate) needs to be further decomposed into PD and LGD components. The

[c] The IRB model can be equivalently regarded as a 1-(latent)-factor probit model. There are efficient estimation methods for the parameters of such models. In particular, a closed-form estimator of the correlation parameter is available.

[d] An alternative yet similar methodology for deriving empirically based asset correlation values is to analyze historical default rates. In essence, this approach would require the estimation of mean and standard deviation of default rates, which in turn can be used directly within the Merton model to derive asset correlation values.

assumption made in this study is that the LGD rate corresponds with the findings from the Basel Committee's quantitative impact studies of the potential Basel II capital charges on banks. The PD value is thus the residual, or EL divided by LGD.

The standard deviation of loss rates must be transformed into the corresponding high quantile (99.9%) UL generated by the IRB formula. The methodological solution becomes one of estimating the loss rate distribution and from this, the mean (or expected loss) and the 99.9th percentile loss (for a technical explanation of the methodology, see the Deriving Empirically Implied Correlations section on page 7). The empirical correlations are then derived across several asset classes, shown in the tables on pages 8 and 9, and compared with the Basel II correlation assumptions in each case.

Deriving Empirically Implied Correlations: A Technical Explanation

Several distributions were fitted to the mean and standard deviation of loss rate data with the beta distribution providing the best fit. This distribution is completely characterized by two parameters, α and β, which are easily obtained from the mean (μ) and standard deviation (σ) of the losses themselves. These quantities are linked as follows.

$$\alpha = \mu \cdot \left(\frac{\mu \cdot (1-\mu)}{\sigma^2} - 1 \right) \tag{1}$$

$$\beta = (1-\mu) \cdot \left(\frac{\mu \cdot (1-\mu)}{\sigma^2} - 1 \right) \tag{2}$$

From the time series of losses by asset class, μ and σ are measured and from Equations 1 and 2 above, α and β are easily estimated. If α and β are known and given the probability density function for a beta distribution:

$$P(x) = \frac{\int_0^x (1-t)^{\beta-1} \cdot t^{\alpha-1} dt}{\mathrm{B}(\alpha,\beta)} = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\cdot\Gamma(\beta)} \cdot \int_0^x (1-t)^{\beta-1} \cdot t^{\alpha-1} dt \qquad 1 \geq x \geq 0, \quad \alpha,\beta > 0 \tag{3}$$

where x is the distribution variable, and Γ is the standard Gamma function evaluated at the relevant parameters, the total losses (EL + UL) are simply the value of x when $P(x) = 99.9\%$ (so chosen to comply with Basel II standards). Subtracting off EL gives the UL.

The Basel II equation for the IRB capital charge for corporates, sovereigns and banks is given by:

$$K = \left(LGD \cdot N\left(\sqrt{\frac{1}{1-\rho}} \cdot \left[N^{-1}(PD) + \sqrt{\rho} \cdot N^{-1}(0.999) \right] \right) - PD \cdot LGD \right) \times SF_{\text{MATURITY}} \tag{4}$$

with correlation defined by $\rho = 0.24 - 0.12 \cdot \left(\frac{1-e^{-50 \cdot PD}}{1-e^{-50}} \right)$, and $\left[\frac{1+(M-2.5)\cdot b}{1-1.5\cdot b} \right]$ a scale factor to adjust for maturity (M) effects. For retail portfolios, Basel II's IRB capital charge equation has no maturity factor, i.e.:

$$K = UL = LGD \cdot N\left(\sqrt{\frac{1}{1-\rho}} \cdot \left[N^{-1}(PD) + \sqrt{\rho} \cdot N^{-1}(0.999) \right] \right) - PD \cdot LGD \tag{5}$$

with $\rho = 0.04$ for qualifying revolving exposures, $\rho = 0.15$ for residential mortgage exposures and $\rho = 0.16 - 0.03 \cdot \left(\frac{1-e^{-35 \cdot PD}}{1-e^{-35}} \right)$ for other retail exposures. In Equation 4, the $PD \cdot LGD$ term represents the EL and the remaining term, $LGD \cdot N\left(\sqrt{\frac{1}{1-\rho}} \cdot \left[N^{-1}(PD) + \sqrt{\rho} \cdot N^{-1}(0.999) \right] \right)$ represents the total losses. The difference between these two measures Basel II's UL.

The asset correlation may be derived by calculating that correlation value which equates the Basel II UL to the empirical UL (using the beta distribution). That is, the correlation equations and constants described above were *not* used, but rather an implied correlation was sought for Equation 4 (or 5) with the constraint that the Basel II equation UL was equal to the fitted beta distribution UL (with fit parameters α and β).

Credit Cards[a]

(%)

	Federal Reserve Loss Rate Data	Structured Finance Loss Rate Data		UK Loss Rate Data
		Prime	Subprime	
Data Sample Period	1985–2007	1991–2007	1996–2007	1994–2007
EL (μ)	4.23	5.44	11.19	0.61
σ	1.02	1.01	3.52	0.32
LGD	71.60	71.60	71.60	85.00
PD	5.90	7.60	15.62	0.72
UL (99.9%)	3.80	3.60	13.45	1.44
ρ	1.32	0.90	3.98	2.58
Basel II Correlation Assumption	4.00	4.00	4.00	4.00

[a]Results from empirically based correlation analysis.
Source: Fitch Ratings, Federal Reserve, Bank of England.

Residential Mortgages[a]

(%)

	Federal Reserve Loss Rate Data	Structured Finance Loss Rate Data by Vintage Year (Through 2005)									UK Loss Rate Data
		Prime			Alt-A			Subprime			
Data Sample Period	1991–2007	2000	2001	2002	2000	2001	2002	2000	2001	2002	1994–2007
EL (μ)	0.15	0.01	0.07	0.02	0.53	0.25	0.11	1.40	1.59	1.45	0.01
σ	0.07	0.01	0.05	0.01	0.37	0.15	0.08	0.52	0.62	0.54	0.01
LGD	20.30	20.30	20.30	20.30	20.30	20.30	20.30	20.30	20.30	20.30	25.00
PD	0.73	0.05	0.33	0.07	2.59	1.22	0.55	6.90	7.81	7.16	0.03
UL	0.29	0.08	0.31	0.06	1.88	0.73	0.38	2.13	2.62	2.25	0.04
ρ	2.07	6.07	4.93	3.18	6.76	4.06	3.85	3.30	3.99	3.44	3.31
Basel II Correlation Assumption	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00

[a]Results from empirically based correlation analysis.
Source: Fitch Ratings, Federal Reserve, Bank of England.

Consumer Lending[a]

(%)

	Federal Reserve Loss Rate Data	Structured Finance Loss Rate Data for Auto Loans		UK Loss Rate Data
		Prime	Subprime	
Data Sample Period	1985–2007	1998–2007	2001–2007	1994–2007
EL (μ)	1.02	1.03	6.69	0.42
σ	0.30	0.27	1.61	0.11
LGD	48.00	48.00	48.00	45.00
PD	2.12	2.15	13.94	0.93
UL	1.18	1.03	5.96	0.40
ρ	1.31	1.05	2.19	0.76
Basel II Correlation Assumption (Function of PD)	9.19	9.13	3.10	12.39

[a]Results from empirically based correlation analysis.
Source: Fitch Ratings, Federal Reserve, Bank of England.

Note: Please see Appendix for a discussion of the important methodological considerations in interpreting the empirically based correlation estimates. Please also note that the PD and LGD values used in the analysis are illustrative examples for decomposing the EL (or mean loss rate) and are not intended to reflect Fitch's view about the average PD and LGD values for each asset class.

Corporates and Commercial Mortgages[a]

	Federal Reserve Loss Rate Data (Commercial Mortgages)	Federal Reserve Loss Rate Data (Corporates)	UK Loss Rate Data (Corporates)
Data Sample Period	1991–2007	1985–2007	1998–2007
EL (μ)	0.44	0.84	0.11
σ	0.70	0.52	0.04
LGD	37.25	37.25	22.00
PD	1.18	2.26	0.52
UL	5.09	2.54	0.26
ρ	18.26	5.15	2.24
Basel II Correlation Assumption (Function of PD)	18.65	15.28	21.25

[a]Results from empirically based correlation analysis.
Source: Fitch Ratings, Federal Reserve, Bank of England.

Key

EL (μ) — Empirically derived mean annualized loss rate, comparable to expected loss. Please note that EL as defined in this analysis, which is simply the calculated mean loss rate, is not to be confused with the EL concept as applied within the structured finance ratings process, which reflects a forward-looking projection of "base case" losses within a portfolio.
σ — Empirically-derived standard deviation of annualized loss rate.
LGD — Loss given-default (or 100% minus the recovery rate).
PD — Probability of default for a one-year horizon, derived by dividing the empirically derived mean annualized loss rate by the LGD assumption.
UL (99.9%) — Estimate of the total loss rate at the 99.9% confidence interval of the assumed Basel II credit loss distribution minus the mean loss rate (or EL).
ρ — Asset correlation estimate implied from the Basel II credit loss distribution.
Basel II correlation assumptions — Regulatory-determined asset correlation values used within the IRB capital formulas.

An alternative approach to deriving implied correlations relies on credit economic capital modeling rather than empirical data analysis. Under this approach, the UL or economic capital for a portfolio is calculated at the 99.9% quantile corresponding with the IRB calibration. After substituting the average PD and LGD of the portfolio into the IRB equation and setting this UL estimate equal to the Basel minimum capital requirement, the asset correlation can be implied in a manner conceptually similar to the empirical loss rate approach used in this study.

An advantage of the economic capital approach is that it applies a forward-looking estimate of UL and helps to overcome some of the shortcomings associated with using historical loss data, namely that empirically based analysis does not necessarily reflect financial product evolution, changes in underwriting standards and future correlation patterns. The economic capital approach, however, requires assumptions about how the particular portfolio credit risk model is designed and parameterized, and introduces potential elements of subjectivity and model variability within this calibration process.

Appropriate Conservatism in Basel II Correlations

Perhaps the most important finding is that the Basel II correlation assumptions exceed the empirically derived correlation values across all asset classes (see the tables on pages 8 and 9). This finding is evident in evaluating the Federal Reserve, Bank of England and US structured finance loss data.

This conservatism is appropriate and likely reflects numerous regulatory policy objectives, such as capturing maturity effects (e.g., for longer-term obligations like residential mortgages) and providing a layer of buffer capital to absorb general risk modeling uncertainty. For example, the higher correlations compensate for potential underestimation of PD and LGD values by IRB banks. The conservatism is also a reflection of the global scope of Basel II and the need for Basel II correlation assumptions to account for potential differences in risk profile across banks, such as for banks operating in non-G10 countries and emerging markets, and for more specialized institutions with less diversified portfolios.

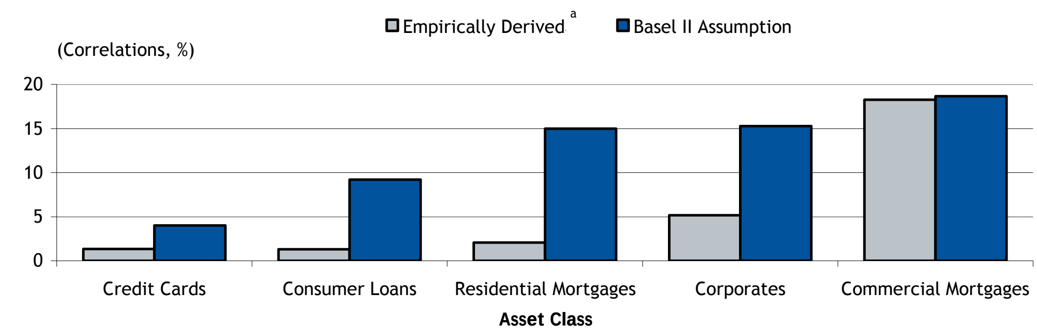
The apparent Basel II conservatism is also appropriate given that the empirically derived correlations in this study are based on long-term data consisting primarily of “normal” market conditions. Of course, co-movement among asset values and defaults increases dramatically during periods of severe financial stress, generating higher volatility in portfolio loss rates. That is, the correlation regime that is appropriate during benign economic times is likely to understate correlation patterns under stress, as assets tend to behave more uniformly and defaults tend to cluster during market downturns. Since capital is most important as a loss absorber during periods of financial stress, the relatively high Basel II correlations generally appear to be prudent. However, it is also important for financial institutions to perform rigorous stress analysis as part of their capital management strategy to consider explicitly scenarios based on higher-than-normal correlation patterns.

Basel II Correlations Consistent with Risk Profile of Different Asset Classes

While on an absolute basis the Basel II correlation assumptions exceed the empirically based correlation results, the relative rank-ordering of Basel II correlation assumptions across asset classes is consistent with these results.

The asset classes with the highest Basel II correlation assumptions (i.e., commercial mortgages and corporates) also generate the highest empirically derived correlation values in the study. For example, the empirically derived correlation value for commercial mortgages (based on Federal Reserve data) is 18.3%, compared with a Basel II correlation assumption of 18.7% (at the 1.18% PD used in the analysis). For corporate exposures, the Basel II correlation assumption of 15.3% (at the 2.26% PD) compares to an empirically derived correlation of 5.2% (based on Federal Reserve data)—quite a large difference in absolute terms, but still relatively higher than the correlations derived for other asset classes. For corporates and commercial mortgages, the relatively high Basel II

Basel II Assumptions Consistent with Empirical Results in Rank-Ordering Correlation Values



[a]Based on Federal Reserve loss rate data.
Source: Basel Committee on Banking Supervision, Federal Reserve, Fitch Ratings.

correlation assumptions likely are designed to capture both heightened sensitivity to common risk factors as well as lower diversification in practice of single-obligor exposure (i.e., the difficulty from a practical standpoint of fully diversifying idiosyncratic risk within bank portfolios of corporate and commercial mortgage lending).

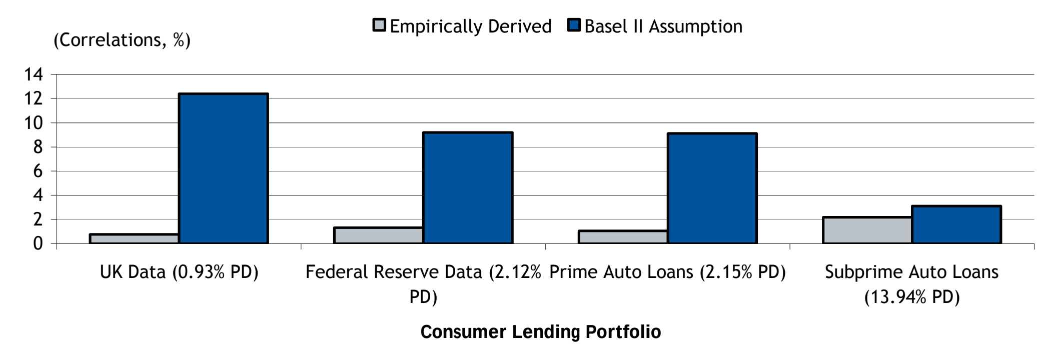
Indeed, the asset classes with relatively lower Basel II correlation assumptions (i.e., credit cards) also generated lower empirically derived correlations. For example, the empirically derived correlation for credit cards (based on Federal Reserve data) is 1.3%, compared with the relatively low Basel II correlation assumption of 4.0% for this asset class. For consumer lending, the empirically derived correlation is also 1.3%, compared with a Basel II assumption of approximately 9% (at the 2.12% PD level). That is, Basel II assumes that consumer lending generally exhibits lower asset correlation than corporate and commercial mortgage lending, and the empirically derived correlation analysis bears out this relative difference in risk profile.

In comparing the capital impact of Basel II across asset classes, it is important to recognize that assets subject to relatively higher correlation assumptions will not necessarily incur higher regulatory capital charges. For example, credit cards exhibit very low correlations and hence low variability in portfolio loss rates; however, the EL or mean portfolio loss rates tend to be quite high. The relatively high PD and high LGD for credit cards means that their Basel II capital charges could in practice exceed the Basel II charges on assets subject to higher correlation assumptions but that are typified by relatively lower PD and LGD values.

No Clear-Cut Relationship Between Correlations and PD

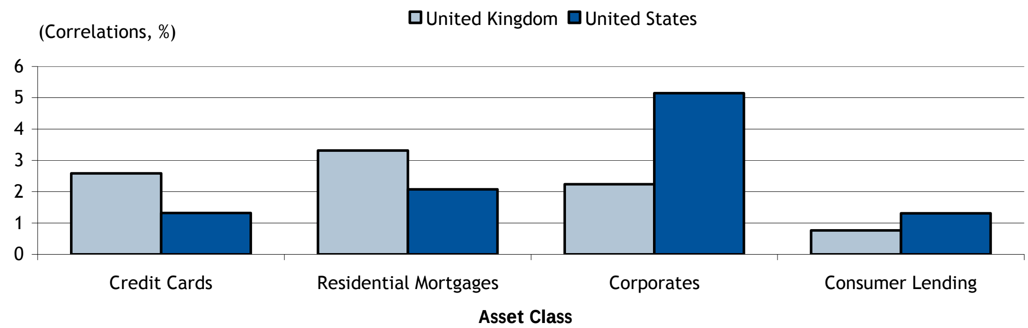
A theoretical assumption incorporated into certain of the IRB formulas is that asset correlations decrease as a function of PD. The logic of Basel II is that, even though on an absolute basis the default risk is greater for lower quality borrowers, the financial performance of these weaker borrowers is assumed to be driven largely by idiosyncratic factors specific to the firm (e.g., poor management, weak credit fundamentals) and is relatively less sensitive to systematic risk factors. Basel II applies this assumption to corporate and commercial mortgage assets (which are subject to the same IRB formula with correlations starting at 24% for very low PD or high quality assets and then decreasing progressively to 12% for higher PD assets) as well as to consumer lending (which ranges from 16% for low PD assets down to 3% for high PD assets). Interestingly, prior consultative drafts also applied ranging correlation assumptions for credit card assets, but the final version of Basel II ultimately provided a fixed correlation assumption of 4% across all PD levels.

Example of Correlations Increasing with PD, Counter to the Basel II Assumptions



Source: Basel Committee on Banking Supervision, Federal Reserve, Fitch Ratings.

Empirically Derived Correlations Vary by Geography (and Asset Class)



Source: Bank of England, Federal Reserve, Basel Committee on Banking Supervison, Fitch Ratings.

To evaluate the relationship between PD and correlations, it is helpful to compare the empirically derived correlation values based on structured finance data for prime versus subprime assets. For example, as illustrated in the chart at the bottom of page 11, the empirically derived correlation value for subprime consumer assets (in this case, auto loans) is 2.2%, significantly higher than for prime assets (about 1%). This result is directionally opposite to the Basel II assumption that lower quality (high PD) consumer loans exhibit lower asset correlations than higher quality (low PD) loans. Similarly, the empirically derived correlation value for subprime credit card lending (3.98%) is higher than for prime lending (0.9%).

The empirically derived correlations for subprime residential mortgages, looking across the 2000–2002 vintages, are generally lower than for prime exposures; however, these differences are relatively small and the volatility in loss rates (and therefore the implied correlations) for prime mortgages is driven by the relatively low mean loss rates experienced in the historical sample used in this study. Additionally, the data set used in this study does not include the still-evolving loss rates from more recent vintages of residential mortgages that are at this stage experiencing higher delinquency rates than is reflected by historical seasoning patterns. While it is relatively early at this stage to collect and statistically evaluate empirical loss rate data relating to recent vintages of subprime mortgage lending (unless extrapolated from delinquency data), anecdotal evidence to date suggests that correlation patterns for the 2006 and 2007 vintages of mortgage lending will exceed empirically based correlations implied by long-run historical loss rates.

The issue of how correlation values relate to PD values is important in practice; however, there does not appear to be conclusive empirical evidence of what the exact statistical relationship is. Part of the likely reason that Basel II regulators decided to deploy variable correlations was to dampen potential pro-cyclicality, so that borrowers whose credit quality weakens during a recession would incur less dramatic increases in capital requirements than if an increasing or constant correlation assumption were applied. A macro-prudential concern with a pro-cyclical capital framework is that lenders facing increasing Basel II charges in a downturn would be pressured to conserve capital, thus curtailing the availability of credit and potentially exacerbating an economic contraction.

Another reason for the Basel II variable correlation assumption is to avoid capital charges on lower quality borrowers ramping up dramatically relative to Basel I, which potentially could increase borrowing costs or lead to the disintermediation of credit for this segment of the market. For example, whereas all corporate assets were subject to a blanket capital charge of 8% under Basel I, borrowers with PDs above 1.3% (assuming 45% LGD) would be subject to an increase in capital charges under Basel II.

Given that the empirical evidence in this study does not seem to support the Basel II assumption that correlations decline as a function of PD, there is the potential that the Basel II correlations might be relatively less conservative for lower quality borrowers. The apparent overall conservatism in the Basel II correlations might help to mitigate some of these concerns; however, it is important for analysts to keep this finding in mind when evaluating Basel II capital charges on non-investment grade or below prime credit portfolios.

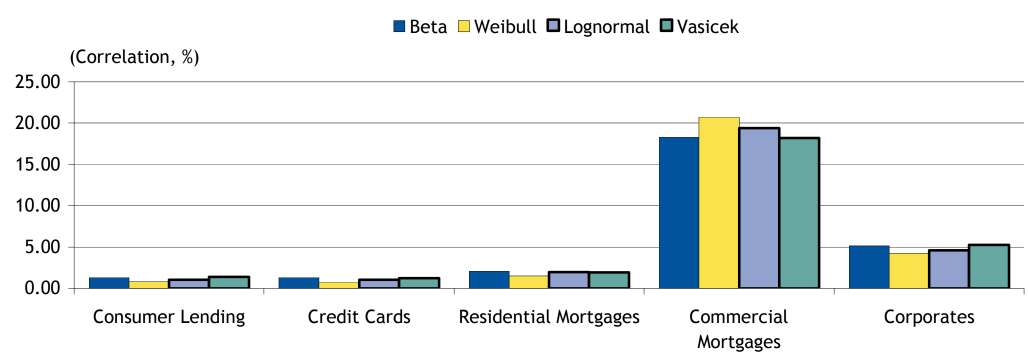
Ongoing empirical study will help to refine the statistical relationship between PD and correlations, particularly when looking across different asset classes and geographic regions. Indeed, a review of the limited yet growing research literature on this issue provides no definitive conclusions regarding the relationship between PD and correlations, with some studies showing a positive statistical relationship and others showing a negative one depending on the asset class and the methodology and dataset used in the particular study.

Correlations Vary Geographically

In the interests of tractability and establishment of a level playing field, Basel II applies the same correlation assumptions globally, irrespective of potential differences in the risk profile of assets across different geographic regions. For example, the same Basel II correlation values are applied to assets originated in Europe, the United States, Latin America and Asia, raising the issue of whether the IRB formulas potentially understate the capital needed to cover UL on portfolios of certain geographically concentrated portfolios. Of particular relevance is sensitivity to risk factors that are unique or that differ across countries and that might be associated with more extreme loss rate volatility than is indicated by the Basel II correlation assumptions.

To assess these potential geographic differences, this study evaluates empirically derived correlations based on both US and UK bank loss rate data. Interestingly, despite the overall similarities between the US and UK economies and financial markets, notable differences in the empirically derived asset correlations are evident. For example, as illustrated in the chart on page 12, the correlations for US assets (based on Federal Reserve data) are higher than the correlations for UK assets (based on Bank of England data) for both consumer lending and corporates. However, for residential mortgages and credit cards, the US correlations are lower than the UK correlations.

Different Distributional Assumptions Generate Similar Implied Correlations



Source: Basel Committee on Banking Supervision, Federal Reserve, Fitch Ratings.

The apparent difference in empirically derived correlations between US and UK assets, although moderate on an absolute basis, is a caveat to the Basel II assumption of applying geographically invariant correlation values. Analyzing differences in correlation across geographic regions therefore is an important element of Pillar 2, under which banks are expected to evaluate the relevance of the Basel II assumptions in assessing internal capital adequacy.

Distributional Assumptions Have Minimal Impact on Results

In addition to the methodological assumption that credit portfolio losses are represented by a beta distribution, the empirical loss data were also tested with the assumption that they followed either a Weibull, a lognormal, or a Vasicek distribution. In each case, the implied correlation was chosen as that value that set the computed UL (from the relevant theoretical distribution) equal to the Basel-calculated UL. As illustrated in the chart at the bottom of page 13, the choice of distributional assumption has a minimal impact on the empirically derived correlation values, indicating that the choice of a beta distribution is appropriate and not a source of the variation in the empirically derived results relative to the Basel II correlation assumptions.

Implications for Evaluating Basel II Capital Ratios of Financial Institutions

The findings within this study have important implications for evaluating the Basel II capital ratios of IRB banks, including within the financial institutions ratings process. While further empirical analysis across additional and more granular dimensions (e.g., by asset class, geography, obligor credit quality, market cyclicality, etc.) would further refine understanding of the appropriateness of the Basel II correlation assumptions, several preliminary conclusions of this study are relevant for analyzing IRB capital levels.

The apparent conservatism of the Basel II correlation assumptions provides a degree of comfort that the IRB ratios are calibrated to deliver prudent minimum levels of capital. At the same time, the credibility and robustness of bank-supplied inputs to the formula (particularly PD and LGD) is paramount to the success of Basel II in promoting minimum capital adequacy. Pervasive underestimation of PD and LGD values could potentially dominate the conservatism in Basel II correlation assumptions, potentially undermining IRB calculations of minimum capital requirements. The rigor of credit risk measurement validation processes is therefore critical. Banks will need to actively monitor the accuracy and consistency of their PD and LGD estimates, for example through statistically analyzing these estimates relative to realized default and loss severity experience, benchmarking them against other types of risk measures, and qualitatively evaluating internal ratings methodologies and practices.

When evaluating Basel II correlations, it is also important to keep in mind that these assumptions are differentiated by regulatory-defined asset classes and that the underlying risk profile of these assets will likely change over time. In other words, the Basel II correlations are static values describing the behavior of dynamic assets whose future loss experience will depend on financial product innovation, changes in key risk factors (e.g., underwriting practices), and structural shifts in financial markets. To the extent that the variability in loss rates increases as a result of these future changes, the Basel II correlation values might become less relevant or robust over time for certain asset classes (or subcategories of those asset classes). Therefore, evaluating the appropriateness of the Basel II correlation assumptions and capital charges going forward depends on active analysis of changes within financial products and markets, particularly those changes that might increase correlations among assets.

A striking finding from this study is that there does not appear to be a consistent relationship between PD and correlation values across asset classes. It is therefore particularly important to assess the appropriateness of the underlying correlation assumptions in cases where Basel II assumes either fixed or decreasing correlations as a function of PD levels, but where the empirical evidence suggests otherwise. For example, for consumer lending, Basel II assumes that correlations decrease at higher PD values; however, the empirical analysis (in this case, for auto loans) suggests a directionally opposite relationship. Such examples, where the Basel assumptions seem to run counter to actual experience, merit particular study when assessing the contextual appropriateness of the IRB correlations and capital charges.

Another important consideration in evaluating the Basel II correlation assumptions is the potential for realized correlations to increase dramatically under periods of financial market stress. By using “hardwired” and predetermined correlation assumptions, the IRB formula implicitly assumes stability in correlation values over time. While the Basel II assumptions appear conservative relative to “through-the-cycle” analysis of empirically derived correlations, it is unclear whether these static assumptions would sufficiently capture a ramp up in correlations during market crises. From a prudential standpoint, the concern is that higher correlations during market distress are manifested in a clustering of defaults and losses which, in turn, pressure financial institutions to shore up risk-based capital ratios at the same moment that raising fresh capital becomes challenging (and expensive).

Stress testing and scenario-based analysis are therefore critical risk management tools for identifying and contemplating the potential impact of a pronounced increase in correlations. In particular, it is important for institutions to evaluate scenarios based on higher risk factor correlations, including the corresponding impact on Basel II capital requirements and economic capital levels. Stress testing is important to both enterprise risk management and to meeting Pillar 2 of Basel II, as an understanding of the impact of potential instability and jumps in correlations should inform banks’ broader internal capital assessment processes.

Ultimately, the evaluation of the Basel II correlation assumptions is fundamental to assessing the relevance and appropriateness of the IRB capital charges, and it is an area where further empirical analysis of these assumptions on a granular and ongoing basis will be beneficial.

Appendix: Methodological Drivers of Correlation Estimates

There are several important methodological considerations to keep in mind when evaluating the empirically based correlation estimates derived within this study.

- The assumptions regarding how mean loss rates (EL) are decomposed into PD and LGD estimates affect the resulting correlation estimate. All else being equal, assuming a lower LGD and, by definition, a higher PD level for a given EL value will result in higher correlation estimates. For example, for the same empirically based mean loss rate of 2%, assuming a 20% PD and 10% LGD will generate a higher correlation estimate than assuming 2% PD and 100% LGD.
- All else being equal, higher absolute levels of mean and standard deviation of loss rates will increase the correlation estimate. For example, a portfolio with a mean loss rate of 4% and a standard deviation of loss of 2% will generate higher correlation estimates than a portfolio with a mean loss rate of 1% and a standard deviation of loss of 0.5%—even though the coefficient of variation (i.e., standard deviation normalized by the mean) is 50% in each case. Thus, the correlation estimates derived in this study do not monotonically increase as a function of the coefficient of variation.
- Depending on the granularity of the data set used, the standard deviation of loss rates might embed a degree of undiversified idiosyncratic risk. That is, if a "lumpy" data set is used in deriving mean and standard deviation of loss rates, the UL (and therefore the correlation estimate) will implicitly reflect exposure to both idiosyncratic and systematic risk factors. For example, if using a data set that is either relatively small or that contains significant single-obligor concentrations, there is a potential of deriving higher empirically derived correlation estimates relative to using a larger, more diversified data set.
- The history or length of the empirical data set used also has a critical impact on the correlation results. There is a clear trade-off involved in using longer data histories, which provide greater statistical robustness but might mask dynamic changes in product attributes and risk factors over time. One potential solution is to weight more heavily the more recent observations within the data set, an approach not explored in this study. Ultimately, however, empirically based approaches are rooted in historical data, and the resulting correlation estimates are not sensitive to current and future changes in risk profile within each product category.
- The distributional assumption (beta, Weibull, lognormal, or Vasicek) has only a moderate impact on the correlation estimates. Different distributions will generate marginally different correlations for the same portfolio.
- The choice of confidence interval, although not evaluated as a variable within this study beyond the 99.9% Basel II assumption, has no impact on the correlation estimate.

References

1. Basel Committee on Banking Supervision, "International Convergence of Capital Measurement and Capital Standards—A Revised Framework," (2005), Bank for International Settlements.

2. Basel Committee on Banking Supervision, "An Explanatory Note on the Basel II IRB Risk Weight Functions," (2005), Bank for International Settlements.

3. Gordy, Michael B., "A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules," (2003), *Journal of Financial Intermediation* 12, 199–232.

4. Vasicek, Oldrich A. "The Distribution of Loan Portfolio Value," (2002), *Risk*, December, 160-162.