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Measuring Concentration Risk – A Partial Portfolio Approach

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MEASURING CONCENTRATION RISK - A PARTIAL PORTFOLIO APPROACH

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ABSTRACT

Concentration risk is an important feature of many banking sectors, especially in emerging and small economies. Under the Basel Framework, Pillar 1 capital requirements for credit risk do not cover concentration risk, and those calculated under the Internal Ratings Based (IRB) approach explicitly exclude it. Banks are expected to compensate for this by autonomously estimating and setting aside appropriate capital buffers, which supervisors are required to assess and possibly challenge within the Pillar 2 process. Inadequate reflection of this risk can lead to insufficient capital levels even when the capital ratios seem high. We propose a flexible technique, based on a combination of "full" credit portfolio modeling and asymptotic results, to calculate capital requirements for name and sector concentration risk in banks' portfolios. The proposed approach lends itself to be used in bilateral surveillance, as a potential area for technical assistance on banking supervision, and as a policy tool to gauge the degree of concentration risk in different banking systems.

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I. Introduction

The concentration risk in banks' credit portfolios arises mainly from two types of imperfect diversification: "name" and sector concentrations (BCBS, 2006b). Name concentration happens when the idiosyncratic risk cannot be perfectly diversified due to large (relative to the size of the portfolio) exposures to individual borrowers. Sector concentration emerges when the portfolio is not perfectly diversified across sectoral factors, corresponding to systematic components of risk.

Concentration risk is relevant for the stability of both individual institutions and whole financial systems. Exposures to large borrowers like Enron and WorldCom contributed to financial problems of several U.S. banks in the early 2000s. A housing crisis combined with concentrated mortgage portfolios resulted in a number of bank failures in Scandinavian countries in the 1990s, and contributed to the global financial crisis of 2007/08.

The Internal Ratings Based approach (IRB) of the Basel capital framework is aimed at capturing general credit risk, but does not incorporate explicitly the concentration risk. The IRB formula is based on the Asymptotic Single Risk Factor (ASRF) model derived from the Vasicek (2002) model, which is—in turn—an extension of the Merton (1974) model of firms' default. The ASRF model has the advantage of being portfolio-invariant, i.e., the capital required for any given loan only depends on the risk of that loan, regardless of the portfolio it is added to. From a regulatory perspective, this property allows the capital charge to be estimated without the need to rely on credit portfolio models. The downside of the model is that it ignores the concentration of exposures in real-world bank portfolios, as the idiosyncratic risk is assumed to be fully diversified. Specifically, the capital charge derived from the ASRF model is the same for banks with different levels of the concentration risk (all other things equal). In Basel II and in Basel III the concentration risk is covered under Pillar 2, focused on interaction between banks' own evaluations of their capital adequacy (ICAAP) and supervisors' subsequent review (SREP). Pillar 2 provides a general framework for dealing with concentration risk (and other types of risk not captured by the ASRF model), but banks and regulators have a large degree of freedom in choosing the quantitative tools to measure the additional capital required to cover concentration risk.

Several model-based and simulation-based methods for calculating capital charges for concentration risk have been proposed over the years. The model-based techniques, usually use second-order approximations of generalized ASRF formulas, are generally conceptually complex, and are based on analytical results that are strongly dependent on the assumptions made. The simulation-based methods, while relatively straightforward in application, are heavily computer-intensive: in order to obtain stable quantile loss estimates, millions of Monte Carlo (MC) iterations are often needed.

In this paper we propose an alternative, "partial portfolio" approach, which tries to extract the best features of the two "worlds" of realistic—but cumbersome—full-portfolio simulations and parsimonious—but inflexible—ASRF approximations. Specifically, within a MC simulation, we maintain the ASRF assumption of diversified idiosyncratic risk for the part of a portfolio ("granular" portion) composed of relatively small exposures, for which the portfolio-invariant characterization of capital charges is a reasonable assumption. For the rest of the portfolio ("non-granular")—comprising the largest exposures—we calculate a fully-fledged Credit VaR based on simulations of the systemic *and* the idiosyncratic risk factors. In other words, we apply the full-fledged, but computer-intensive portfolio simulations only to the part of the portfolio where the concentration risk really matters, thus reducing the computational burden.

In the MC setting this translates into generation of pseudo-realizations of the single-risk factor and their use as an input both for calculation of the conditional expected loss (based on the IRB formula) in the "granular" part of the portfolio, and for the simulation of asset value returns of the obligors in the "non-granular" part. The portfolio Credit VaR at the confidence level α is hence obtained as the α-percentile of losses generated by the simulations, minus the expected loss for the whole portfolio. When compared with the outcome of the IRB approach, which uses the ASRF capital formula for all exposures in the portfolio, the Credit VaR calculation captures the potential increase in the portfolio's credit risk caused by name or sector concentration: the difference between the two thus represents the additional capital required to cover concentration risk.

Our paper is close in spirit to Gordy and Lütkebohmert (2013), who calculate additional regulatory capital against concentration risk only on the basis of the largest exposures. However, their method uses analytical approximations of a generalization of the ASRF model and, hence, it suffers from the same limitations as all other model-based methods, i.e., the lack of flexibility of the analytical solutions. For example, introduction of a new set of assumptions—such as Loss Given Defaults correlated with the systemic factor—requires derivation of new formulas for additional capital, with no guarantee that a tractable solution (for regulatory purposes) can be identified. Our proposed approach, by using analytical IRB formulas *within* the MC simulations, allows for reduction of the computational burden, while maintaining the flexibility characterizing simulation-based methods.

We test the partial portfolio approach by applying it to two sets of portfolios (a synthetic portfolio of corporate exposures, and a set of semi-hypothetical portfolios), and comparing the resulting granularity adjustment (GA) with the IRB regulatory capital, as well as with the GA obtained using the Gordy and Lütkebohmert (2013) method.

The maximum GA we obtain for the name concentration risk reaches 6.7 percent of the IRB regulatory capital: this means that the capital requirement should be increased by 6.7 percent to take concentration risk into account. For the sectoral concentration, where the GA can be either positive or negative, we obtain adjustments—beyond those required for name concentration risk—in the range of -0.75 percent to 0.8 percent of IRB capital. We find that the size of the GA depends on the parameter assumptions (in particular if parameters are considered stochastic or deterministic). Our GA estimates are comparable to the GAs obtained using the Gordy and Lütkebohmert (2013) method. Our GA estimates are also closely aligned with the Herfindal-Hirschmann Index (HHI) of credit concentration, which supports the approach adopted by a number of supervisory authorities, of creating benchmark models based on a well-calibrated mapping between a bank's HHI and the granularity adjustment.

The rest of this paper is organized as follows. In Section II we discuss the treatment of the concentration risk in Basel II and Basel III, and the proposed quantitative methods for calculating capital charges for concentration risk. In Section III we present the partial portfolio approach to concentration risk. Application of the method to hypothetical and semi-hypothetical portfolios is presented in Section IV. Section V concludes.

II. Concentration Risk in the Basel Capital Framework

In this Section we discuss the main assumptions of the ASRF model underlying the Basel capital framework under its Pillar 1 (subsection A). We then present the methods of dealing with the name and sector concentration risk proposed in the literature (subsections B and C), and compare them with the current treatment of concentration risk under Pillar 2 of Basel II and Basel III (subsection D).

A. The Asymptotic Single Risk Factor Approach

In 1999 the Basel Committee issued its first consultation paper proposing a complete overhaul of the capital framework—first established in 1988 (BCBS, 1999). The paper recognized that "*for some sophisticated banks, use of internal credit ratings and, at a later stage, portfolio models could contribute to a more accurate assessment of a bank's capital requirement in relation to its particular risk profile*" (ibid., para. 2).

At that time the Basel Committee recognized that risk measurement techniques had advanced significantly among the largest and most sophisticated international banks, and that an "internal model option" for regulatory capital requirements could incentivize sounder risk management practices.

The "full-portfolio option"—the possibility granted to banks to compute their capital requirements straight out of their Value at Risk (VaR) models—looked as a natural one for market risk, given a certain degree of standardization of the underlying conceptual framework (especially after the publication of J.P. Morgan's RiskMetrics technical document[2]) and the relative abundance of the data needed as input to the models (volatilities and correlations, which could be easily estimated daily for most assets).

For credit risk a similar approach looked much less justifiable: techniques for credit risk portfolio modeling had evolved significantly in the second half of the 1990s, but were far from being as standardized as those applied to market risk. Moreover, defaults—which are the most relevant events from the credit risk perspective—are relatively rare, compared to market factors, and much more difficult to track and measure.

[2] RiskMetrics Group (1996), "*RiskMetrics – Technical Document,*" New York: J.P. Morgan.

The modeling challenges were considered serious, though affordable, for the estimation of "first-order" measures of risk (mainly probabilities of default, recovery rates and credit conversion factors), but almost insurmountable for the estimation of "second-order" measures of risk (i.e., volatilities and correlations), which are essential ingredients of any portfolio approach. These considerations prompted the Basel Committee to leave to an unspecified future date the possible adoption of credit portfolio models for regulatory purposes.

By discarding the full-portfolio approach—which would have allowed to use the output of credit VaR models directly as a measure of the capital requirement—and allowing instead the use of internal ratings, the Committee was aware that it had to figure out an alternative way to link capital requirements with internal ratings. The solution came in the form of the Asymptotic Single Risk Factor (ASRF) approach to the objectives of regulation (BCBS, 2001).

The ASRF model traces back to the contributions of Vasicek (2002) and Merton (1974). Its basic intuition is that the creditworthiness of all borrowers (obligors) can be seen, in the first approximation, as depending on a single common risk factor (X)—similarly to the Capital Asset Pricing Model, where all equity securities are seen as co-moving, based on their *beta*, with the market index.

In the ASRF model, for each obligor $i=1,...,n$ in the portfolio, the standardized return on the market value of its assets, Y_i, can be described as

$$Y_i = w_i \cdot x + \sqrt{1 - w_i^2} \cdot \varepsilon_i, \quad (1)$$

$$X \sim N[0,1]; \; \varepsilon_i \sim N[0,1], \quad (2)$$

$$E[\varepsilon_i, \varepsilon_j] = 0 \; \forall i, j, \qquad (3)$$

$$E[X, \varepsilon_i] = 0 \; \forall i, \qquad (4)$$

Where ε_i is an idiosyncratic risk realization, x is a realization of the common risk factor X, w_i is the single obligor's asset correlation with the systematic risk factor, and $w_i w_j$ is the pairwise asset correlation between obligors i and j. The obligor i defaults when the market value of its assets falls below a threshold, calculated by inverting obligor's unconditional probability of default $\overline{PD}_i$.Thus, the default threshold is equivalent to a quantile, α_i, of a standard normal variable,

$$\alpha_i = \Phi^{-1}(\overline{PD}_i), \quad (5)$$

and the default happens when the firm experiences an asset return lower than α_i, i.e.,

$$Y_i = w_i \cdot x + \sqrt{1 - w_i^2} \cdot \varepsilon_i < \alpha_i = \Phi^{-1}(\overline{PD}_i),$$
$$\Leftrightarrow$$
$$\varepsilon_i < \frac{\Phi^{-1}(\overline{PD}_i) - w_i \cdot x}{\sqrt{1 - w_i^2}}. \qquad (6)$$

The conditional probability of default (*PD*, conditional on the realization x of *X*) can be then expressed as

$$PD_i(X = x) = \Phi\left(\frac{\Phi^{-1}(\overline{PD}_i) - w_i \cdot x}{\sqrt{1 - w_i^2}}\right). \qquad (7)$$

Conditional on the realization of the single risk factor, all obligors are independent by assumptions (3)-(4). This, coupled with the assumption that the portfolio is "infinitely granular" (i.e., that no risk exposure "dominates" any other one), and with the monotonic nature of the function linking *PDs* to *X*, allows to apply the law of large numbers to the problem and to approximate the Credit VaR of the portfolio at a given percentile *q* with the expected loss of that portfolio, conditional on the realization of *X* at that percentile (x_q).Using information on exposures at default (EADs) and their loss given default (LGD), this conditional expected loss (CEL) can be easily computed for each obligor as

$$CEL_i(x_q) = PD_i(x_q) \cdot LGD_i \cdot EAD_i = \Phi\left(\frac{\Phi^{-1}(\overline{PD}_i) - w_i \cdot x_q}{\sqrt{1 - w_i^2}}\right) \cdot LGD_i \cdot EAD_i. \qquad (8)$$

With the further assumption that the factor loadings are identical among obligors, $w_i = w$, the whole dependence structure of the portfolio is synthesized by a (common) pairwise asset correlation of $\rho = w^2$ among all obligors. Finally, the regulatory capital, *K*, in the ASRF model is simply equal to the total CEL of the portfolio minus the unconditional expected loss ($EL_i = \overline{PD}_i \cdot LGD_i \cdot EAD_i$),

$$K = \sum_{i=1}^{n} \left[CEL_i(x_q) - EL_i\right]. \qquad (9)$$

B. Name Concentration

A small size of a portfolio or a large size of individual exposures leads to imperfect diversification of the idiosyncratic risk. Naturally, the presence of idiosyncratic (also called name concentration) risk violates the assumption of the "infinitely-granular" bank portfolio in the ASRF model. As in the real world most—if not all—bank portfolios are only finitely granular; thus, the capital charges calculated according to Basel II and Basel III regulations can be understated.

The existing literature proposes several methods of extending the ASRF model in order to calculate additional capital charges against the name concentration risk. These granularity adjustment (GA) strategies can be divided into three groups: heuristic, simulation-based, and model-based asymptotic methods.

Heuristic methods use simple measures of concentration, such as the HHI and the Gini coefficient, to calculate the GA. Typically, the additional capital charge increases linearly in the concentration measure. Heuristic methods are easy to implement, and the empirical evidence suggests that they yield granularity adjustments close to values derived from more calculation-intensive asymptotic methods, especially for relatively large portfolios (Deutsche Bundesbank, 2006). A considerable drawback of the heuristic measures is that they are not sensitive to changes in obligors' characteristics, such as PDs and LGDs, which directly affect the concentration risk.

Model-based asymptotic methods use analytical approximation techniques to derive closed-form formulas for the GA. Gordy (2004) breaks down the Value at Risk (VaR) formula in the ASRF model into a systematic and an idiosyncratic component.[3] The latter is then approximated by a second-order Taylor expansion around the desired quantile value of the systematic component. Emmer and Tasche (2005) propose an extension of the CreditMetrics model where the idiosyncratic risk contribution is calculated for each exposure separately. The derived GA varies also with the size of the exposure relative to the portfolio.

Generally, a big obstacle for the application of model-based methods is the high complexity of analytical formulas. In this respect, Gordy and Lütkebohmert (2013) present a revised closed-form GA formula aimed at reducing the computational effort. In their simplified approach the additional capital is calculated on the basis of only the m largest exposures in the portfolio, and thereby the availability of analytical data is needed only for a subset of obligors. Banks can be permitted to choose m, where higher capital charges (small m) are weighted against heavier data collection burden (large m).

Nevertheless, the most important disadvantage of model-based methods—the lack of flexibility—still remains. As said, the introduction of new assumptions to any model-based framework—also for the simplified methods, such as Gordy and Lütkebohmert (2013)—requires new derivations of the GA formulas, and it is not guaranteed that an analytical solution to the new model set-up exists.

Monte Carlo (MC) simulations can be applied in order to avoid the computation of complex GA formulas. The MC-based GA is estimated as the difference between the Credit VaR from the simulated portfolio loss distribution and the required capital from the ASRF model. While relatively straightforward and flexible in application, MC simulations are heavily

[3] In the baseline ASRF model the idiosyncratic component vanishes as a result of the infinite granularity assumption.

computer-intensive: in order to obtain stable quantile loss estimates, millions of iterations are often needed.

C. Sector Concentration

Another departure from the assumptions of the ASRF model stems from the sector concentration risk, which arises from exposures to multiple, imperfectly correlated sectors. Intuitively, as different geographic regions and industries vary in the level of risk, and often follow different economic cycles, exposures to them do not contribute equally to the portfolio's credit risk.

The sector concentration constitutes a direct violation of the single systematic risk factor assumption of the ASRF model, potentially leading to under- or overstated capital charges. The available methods for incorporating sector concentration risk in the regulatory capital calculations can be divided into multi-factor model adjustments, adjustments of closed-form single-factor models, and MC simulations.

Multi-factor models typically do not offer closed-form solutions. In order to avoid computation-intensive MC simulations, some authors propose simplifying assumptions that result in tractable approximations of the true solution to a multi-factor model. For example, Pykhtin (2004) assumes that all exposures within the same sector are equally exposed to different sector risk factors. Düllmann and Masschelein (2006) simplify his approach further by requiring the same PD and size for exposures within a sector.

Adjustments of the single-factor model, such as ad-hoc scaling factors and mapping techniques, allow for calculating additional capital without estimating a full-blown multi-factor model. The binomial expansion technique (BET) by Moody's is based on proper calibration of a few model parameters which allows for a mapping of the multi-factor risk portfolio into a portfolio with homogenous and uncorrelated exposures. Garcia Cespedes et al. (2005) apply a scaling factor to the ASRF model, which is a function of the sector distribution and sector correlations in the underlying portfolio.

D. Treatment of Concentration Risk under Basel II and Basel III

Basel regulatory standards provide only broad guidelines for managing the concentration risk. Even without a formal GA, a due consideration of concentration risk is not, of course, omitted in the Basel framework: it is clearly addressed as one of the "*risks considered under Pillar 1 that are not fully captured by the Pillar 1 process*" (BCBS 2006a, par. 724). The solution envisaged by the Basel Committee entails treatment of the concentration risk under the Pillar 2, which is based on a bank's ICAAP (Internal Capital Adequacy Assessment Process) and on the SREP (Supervisory Review and Evaluation Process) conducted by the bank's supervisor based on the same ICAAP and on any further relevant evidence (e.g., from public data, supervisory reports, peer group comparisons, etc.). Pillar 2 requires banks to have in place internal procedures to measure and control risk concentrations, and to consult any concentration issues with their supervisory authorities. However, it does not offer specific requirements or guidelines regarding the applicable measurement methods, giving national regulators freedom to set their own rules. As a result, the methodological treatment of the concentration risk differs across banks and across countries.

In practice, banks apply both model-based and heuristic methods to manage the concentration risk. A survey conducted by the Basel Committee in 2006 (BCBS, 2006b) revealed that tools used by banks to manage the concentration risk include internal model-based methods, heuristic measures, but also pricing tools, exposure limits, and stress tests. Pricing tools take the concentration risk into account when pricing the new exposures, while exposure limits put caps on the size of the bank's exposure against a single obligor. Stress tests allow banks to indirectly evaluate their exposure to concentration risk by estimating losses in case of defaults among top largest obligors, or simultaneous defaults of a large proportion of obligors.

National regulators have developed their own practices for the assessment of the methods used by banks to manage the concentration risk. According to a survey conducted by the European Banking Authority (EBA, 2014) many regulators (Bank of Italy, DNB in the Netherlands, among others) use the HHI (which is equal to the sum of squared shares of individual exposures in a portfolio) to evaluate the concentration risk values and the required capital adjustments reported by financial institutions. The Spanish Central Bank (EBA, 2014) and the British Prudential Regulation Authority (PRA, 2015) provide reference tables with additional capital charges corresponding to intervals of the HHI measure for name, sector, and geographic concentration risks. When banks' own estimates of the additional regulatory capital are too different from the regulators' guidelines, banks may be requested to adjust capital ratios. The Swedish Finansinspektionen proposes continuous formulas based on the HHI and—in case of banks using IRB and for the name concentration risk only—based on the Gordy and Lütkebohmert (2013) capital adjustment equation (Finansinspektionen, 2015). The Swedish regulator imposes the calculation formulas on banks, who are required to use them for name, sector and geographic concentration risk capital adjustments.

The Central Bank of Hungary evaluates parameter assumptions of banks' internal models using historical data, and compares banks' calculations with own simulation techniques (EBA, 2014). The Estonian Financial Supervision Authority and the Bank of Italy ask banks to perform stress tests as a part of the concentration risk evaluation exercise, while the Bank of Portugal requires financial institutions to hold additional capital against significant exposures to individual counterparties.

Regarding large exposures, in 2014 the Basel Committee announced new standards for exposure limits (BCBS, 2014). According to the new rules, banks have to report all "large" exposures, i.e., exceeding 10 percent of the Tier 1 capital. At the same time, the value of an exposure to a single counterparty cannot exceed 25 percent of the Tier 1 capital, and

15 percent of the Tier 1 capital in case of banks classified as globally systematically important.[4]

III. A Partial Portfolio Approach to Concentration Risk

As noticed earlier, we propose a new approach to calculating regulatory capital that takes account of the granularity of real-world bank portfolios, while reducing the computational burden associated with numerical methods.

In our approach, we divide a portfolio into two parts: a non-granular sub-portfolio, consisting of the *m* largest exposures, and a granular (diversified) sub-portfolio, containing the remaining positions. The division of the portfolio into the two parts limits the use of computation-intensive simulations to the *m* largest exposures only. In particular, while the capital charge for both parts is calculated using MC simulations, the systemic *and* the idiosyncratic risk factors' draws are used only for the non-granular portfolio, which allows for capturing the effect of exposures' size on regulatory capital where it really matters. The capital charge for the granular portfolio is obtained using the CEL formula in equation (8), i.e., using aggregate PD, LGD and EAD values, for a given realization of the systemic risk factor. This allows for a reduction of computational burden and for modeling simplification of the MC simulations.

The implementation of the method, for a portfolio composed of *n* exposures and with a non-granular sub-portfolio composed of *m* exposures ($m << n$), can be summarized in the following steps.

After choosing the number of portfolio loss simulations *S*, for each iteration *s*:

a) Generate a value for the systemic risk realization, X_s, drawing from *N[0,1]*.

b) For each exposure in the non-granular part of the portfolio, $i \in \{1, \dots, m\}$, simulate the standardized asset return $Y_{s,i}$ by generating an idiosyncratic shock realization $\varepsilon_{s,i}$.[5]

c) Applying equation (6)[6], compare the simulated return with the obligor-specific PD threshold: if exposure *i* defaults, i.e., if $Y_{s,i} < N^{-1}(\overline{PD}_i)$, calculate the loss for the exposure as $LGD_i \cdot EAD_i$.

[4] The list of Globally Systematically Important Banks (G-SIBs) is published every year by the Financial Stability Board (FSB).

[5] In order to capture residual pairwise correlations (either positive or negative), beyond those implied by the common dependence on the systematic factor, the $\varepsilon_{s,i}$ can be generated as correlated draws by using a partial correlation matrix (see Section IV. B).

[6] Whenever the specific asset correlation of obligor *i* is available, it can be used instead of the "standard" IRB correlation (BCBS 2006, paragraphs 272 for corporate exposures and 330 for retail exposures).

d) The total loss for the non-granular portfolio is then

$$Loss_s^{non-granular} = \sum_{i=1}^{m} LGD_i \cdot EAD_i \cdot \bar{\mathrm{I}}(\, Y_{s,i} < N^{-1}(\overline{PD}_i)) \,,$$

where $\bar{\mathrm{I}}(\cdot)$ is an indicator function equal to 1 if the exposure *i* is in default, and zero otherwise.

e) Use the CEL formula (8) to compute the loss (conditional on X_s) for the granular part of the portfolio, $i \in \{m+1, \dots, n\}$:

$$Loss_s^{granular} = \sum_k LGD_k \cdot N\left[\frac{N^{-1}(\overline{PD}_k) - w_k \cdot X_s}{\sqrt{1-w_k^2}}\right] \cdot \sum_{i \in k} EAD_i,$$

where *k* stands for a group of obligors (a whole asset class, a sector, a rating bucket, depending on the information available) characterized by the same values of LGD, PD, and correlation parameters.

f) Sum up losses from the two sub-portfolios to get the total loss for the portfolio in iteration *s*.

At the end of the simulation the given quantile (99.9 percent under Basel) is calculated on the portfolio loss distribution, and the expected loss is subtracted from the quantile loss to obtain the required Credit VaR.

The method is flexible, and can be easily adjusted depending on the available data. For example, the obligor-specific LGDs in the non-granular portfolio can be replaced by draws from a specific distribution, while the asset correlations (w_i^2) can follow from Basel formulas, be calculated based on available historical data, or inferred from market-based observations. At the same time the number of exposures in the non-granular portfolio (*m*) can be set as a fixed fraction of the whole portfolio, or depend on reaching a certain size threshold.

IV. Testing the Approach

We test the partial portfolio approach (PPA) by applying it to two sets of portfolios, and comparing the resulting granularity adjustment and capital charges with the IRB regulatory capital, and with the granularity adjustment proposed by Gordy and Lütkebohmert (2013).

A. Application to a Synthetic Portfolio

First, we apply the PPA to a synthetic portfolio of corporate exposures first used by the International Association of Credit Portfolio Managers (IACPM) and the International Swaps and Derivatives Association (ISDA) for their study of credit capital models (IACPM-ISDA, 2006).

Data

Table 1 presents a summary of the portfolio characteristics.

Table 1. Characteristics of the IACPM-ISDA 2006 Portfolio

Portfolio Summary	
Portfolio Summary	$100 Billion
Number of Exposures	6000 (2 per obligor)
Number of Obligors	3000
Credit Rating	8 rating buckets, average = BBB
Number of Industries	61 (M-KMV classification)
Number of Countries	7
Exposures Characteristics	
LGD	22% to 58% (average = 41%)
Mean Size (standard deviation)	$16.7 million ($101.7 million)
Smallest Exposure/Largest Exposure	$1 million / $1,250 million
Mean Maturity	2.5 years
Shortest Maturity/Longest Maturity	6 months / 7 years
Correlation (R^2)	Average = 20%

When deriving capital charges according to both the PPA, and the IRB formula, we use LGDs and (annualized) PDs provided in the IACPM-ISDA dataset. The database also contains estimates of the exposure-specific correlation with the systemic risk factor (w_i). However, in order to facilitate comparison between the two methods and to focus on the name concentration only, we apply the Basel correlation formula also in the portfolio simulations. For simplicity, we calculate capital charges assuming that all exposures in the portfolio have a maturity of one year. Finally, the estimates of Credit VaR (CVaR) for the partial portfolio approach are based on 100,000 simulations of portfolio losses (with importance sampling).

Results

Table 2 presents regulatory capital based on the IRB formula, and the CVaR calculated using the PPA with three different sizes of the non-granular portfolio, *m*. In the first row the total capital charge is calculated using the non-granular portfolio algorithm only (i.e., with all *3000* obligors in the non-granular part of the portfolio). In the second case we classify as large those obligors whose exposure share in the total portfolio is at least 0.05 of a percent. This results in *m=291* obligors in the non-granular portfolio. In the third case we increase the threshold to 0.5 of a percent, which gives 19 exposures assigned to the non-granular part.

Table 2. Regulatory Capital: Partial Portfolio Method versus IRB Model				
Method	Number of obligors in the non-granular portfolio (*m*)	Credit VaR ($ millions)	Percent difference compared to IRB	Computing time (sec)
Partial portfolio with threshold=0%	3000	3,347	6.7	145
Partial portfolio with threshold=0.05%	291	3,331	6.3	128
Partial portfolio with threshold=0.5%	19	3,322	3.1	127
IRB approach	0	3,230	-	-

By construction, because it accounts for positive idiosyncratic risk, CVaR estimated using the PPA is higher than the regulatory capital calculated using the IRB model (column 3 in Table 2). The difference in capital between the two methods—presented as a percent of the IRB capital charge in column 4—increases in the number of obligors in the non-granular portfolio. It reaches 6.7 percent of the IRB regulatory capital when the fully-blown MC simulations are used to calculate capital charge for all exposures in the portfolio (*m=3000*).

In Figure 1 we plot the calculated CVaR as a function of the size threshold used for the non-granular portfolio. As it can be seen, the CVaR estimated according to the PPA converges towards the IRB capital around the size threshold for non-granular exposures of one percent: at this value there are only four (largest) obligors in the non-granular portfolio. In practice, this kind of analysis, when applied to a range of real portfolios, could also help single out a threshold—in terms of share of total portfolio—below which treating exposures as non-granular would entail a negligible marginal adjustment for concentration risk: this could help to decide how many exposures in portfolio need to be considered individually (e.g., for credit portfolio modeling) and also to verify the adequacy of the regulatory threshold for large exposures in specific portfolios.[7]

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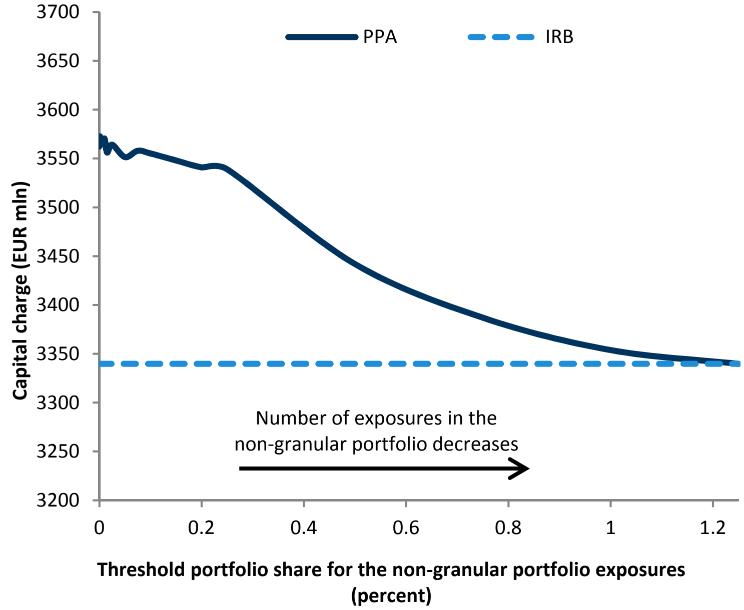
[7] The Basel Committee defines a large exposure as "*The sum of all exposure values of a bank to a counterparty or to a group of connected counterparties (..) if it is equal to or above 10 percent of the bank's eligible capital base*" (BCBS, 2014).

Figure 1. Partial Portfolio Approach: Credit VaR for Varying *m*

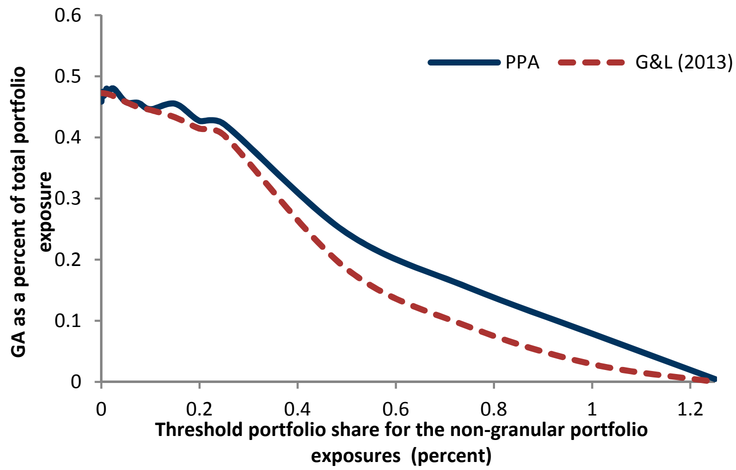


As a benchmark, we compare our results with the GA computed as proposed by Gordy and Lütkebohmert (2013). That is, we recalculate capital charges for the IACPM-ISDA portfolio by applying their simplified, analytical expression for the GA (equation 17, p. 46) to the non-granular portfolio part. To facilitate comparison, we adopt the same parameterization as proposed in their paper, with $\gamma = 0.25$ and $\xi = 0.25$.[8] Figure 2 presents the resulting GA[9] for different sizes of the non-granular portfolio.

[8] The parameter γ links LGD volatility to its expected value, while ξ determines the variance of the systematic factor.

[9] $GA = \frac{K^{partial\,portfolio} - K^{IRB}}{\sum_{i=1}^{n} EAD_i}$.

Figure 2. Granularity Adjustment of Partial Portfolio and G&L (2013) Methods



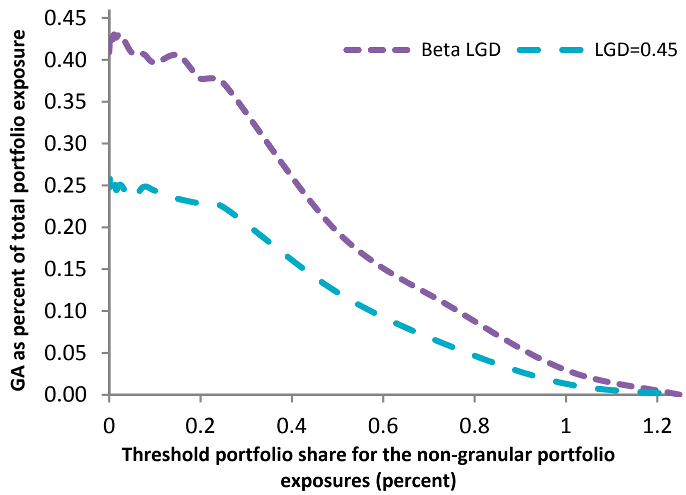
The two approaches provide very similar results, with the GA based on PPA slightly higher than the GA proposed by Gordy and Lütkebohmert.[10] The similarity of the two methods confirms validity of the GAs obtained using out approach. At the same time, the PPA maintains the flexibility characterizing simulation-based methods, which the Gordy and Lütkebohmert (2013) method lacks.

Sensitivity analysis

Next we investigate the sensitivity of the partial portfolio method. First, we replace LGDs provided in the ICAPM-ISDA database with two alternative assumptions: i) a fixed LGD level of 0.45 (corresponding to the LGD for senior, unsecured claims on corporate, sovereign, and bank exposures under the IRB approach), and ii) draws of LGDs from a beta distribution, with parameters for each exposure provided in the IACPM-ISDA dataset. Figure 3 presents the GA of the CVaR calculated under the new assumptions (naturally, the level of IRB capital changes with LGD assumptions too).

[10]Another application of the PPA could be for calibration of Gordy and Lütkebohmert (2013) GA parameters.

Figure 3. Partial Portfolio Approach: Credit VaR for Varying *m* and Different LGD Assumptions



As expected, the GA is sensitive to assumptions about the parameters (in particular if considered deterministic or stochastic): as the example shows, variability in the input parameters—LGD in this particular case—increases the CVaR (and, hence, the size of the GA). Moreover, the considerable difference between the GAs depicted in Figure 3 indicates the impact of introducing elements of randomness (random draws of LGDs from beta distribution in this case) for the estimates of CVaR based on simulation methods.

B. Application to Semi-Hypothetical Portfolios

In this section we apply our proposed partial portfolio approach to a set of semi-hypothetical portfolios, used in a recent IMF study on concentration risk in the Gulf Cooperation Council (GCC) banks (IMF, 2014).

Data

The partial portfolio Credit VaR and the IRB capital requirement are calculated for a set of semi-hypothetical portfolios of a group of 31 large banks in Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and UAE. A full list of banks is presented in Table A.1 in the Appendix; Table 3 shows, country by country, the number of firms extracted from the Moody's KMV database and used for the analysis, together with their average expected default frequencies (EDFs) in 2013 and over a longer horizon, and average asset correlations with the systematic factor (for firms with a large number of missing observations, asset correlations have been approximated with the average ones of the sector they belong to).

Table 3. Characteristics of Semi-Hypothetical Portfolios

	Number of firms	Average EDF by end 2013 (percent)	Long-term average EDF* (percent)	Average asset correlation
Bahrain	29	0.52	1.10	0.12
Kuwait	166	1.12	2.93	0.15
Oman	75	1.78	---	0.17
Qatar	42	0.10	0.54	0.27
Saudi Arabia	155	0.16	0.46	0.30
UAE	87	0.61	1.98	0.26

(*): 2006-2014 for Saudi Arabia, 2009-2014 for the other countries (except for Oman, for which not enough data were available, so the EDFs of Omani firms were scaled up by a factor of 3.25, equal to the average of the scaling factors for the other countries).

Source: Moody's KMV and IMF staff calculations.

As regards the composition of banks' portfolios, in the absence of specific information we generate semi-hypothetical portfolios. For this aim, we use two available data sources: listed companies' total debt (as observed in Moody's KMV database) and banks' loan breakdown by sector (as drawn from banks' publicly disclosed documents).

As detailed name-by-name exposures are not available, we adopt a number of assumptions to construct plausible loan portfolios—hence dubbed "semi-hypothetical"—drawing from available information on publicly listed companies. In particular, we assume that in each country listed companies' total debt is financed by domestic banks in a percentage consistent with the share of foreign claims by Advanced Economy (AE) banks on total local company exposures, i.e., that corporate debt not financed by AE banks is entirely financed by domestic ones. The assumed shares of companies' debt financed by domestic banks are given in Table 4.

Table 4. Bank Funding of Domestic Companies in Semi-Hypothetical Portfolios

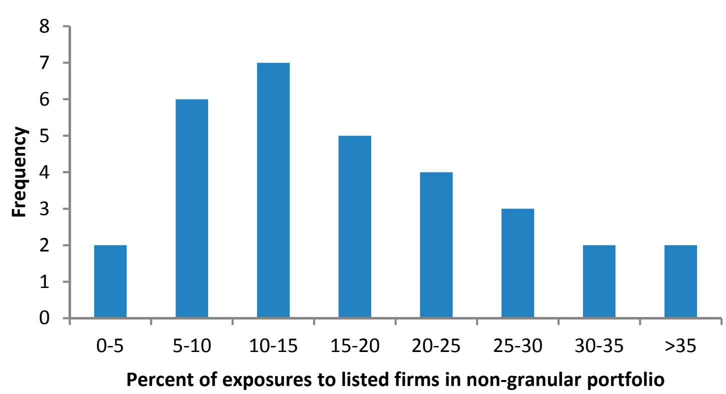
	Assumed share of listed companies' debt financed by domestic banks (percent)
Bahrain	75
Kuwait	90
Oman	50
Qatar	75
Saudi Arabia	70
UAE	50

End-2013 EDFs are extracted from the Moody's KMV database and rescaled according to long-term averages in 2006-14 (Table 3). The companies are grouped in sectors according to the Pillar 3 sector classification adopted by banks and it is assumed that each bank grants loans to firms in each sector according to its share of loans to that sector with respect to the whole banking system.[11]

For simplicity, the LGD is set at 45 percent. Also, we assume that all exposures have 1 year maturity. Finally, for each country the latent systematic factor is approximated by the total market asset value of listed firms, as estimated in the Moody's KMV database. The asset correlation with the systemic factor is estimated, for each firm, as the correlation between the monthly changes of the firm's market value of assets and the monthly changes in the total market value of assets.

Based on the assumptions, we obtain a non-granular part of the portfolio with obligors individually identified in terms of creditworthiness (through EDFs) and dependence on the latent systemic factor (through the asset value correlations). The remaining part of each bank's credit portfolio, not allocated to listed companies, is considered as "granular" and treated accordingly. Naturally, this might not be necessarily accurate for the banks examined, as they could have significant exposures towards non-listed companies and other relevant obligors (including public entities). However, we consider it an acceptable assumption for the illustrative purposes of this exercise. The chart below reports the shares of the non-granular portions of the portfolios.

Figure 4. Share of Non-Granular Part of Loan Portfolios



Estimation

The results for the PPA are based on Monte Carlo simulations with 100,000 iterations and adoption of importance sampling to reduce the variance of estimates.

[11] For example, if sector X is financed 20 percent by bank A and 30 percent by bank B, the debt of a firm in sector X is assumed to be financed (entirely or partially) 20 percent by the former bank and 30 percent by the latter.

Two different kinds of Credit VaR are estimated: with asset correlations calculated according to the regulatory IRB formula (CVaR-IRB), and with asset correlations estimated from the Moody's KMV database (CVaR-MKMV). The former, as already discussed, allows to appreciate the effect of portfolio coarseness in isolation and, hence, when compared with the IRB capital, to infer the impact of name concentration.

The second measure (CVaR-MKMV) allows to capture—through the difference with respect to CVaR-IRB—the impact of sector concentration, as resulting from the use of market-based asset correlations for each firm in the non-granular part of the portfolio, coupled with the consideration of their actual (though semi-hypothetical) exposures.[12]

The interpretation of the difference between the two CVaR measures as an indicator of sector concentration requires a caveat: as discussed in length in BCBS (2006b), to be properly addressed, sector concentration should be measured within a multi-factor modeling framework, as opposed to the single-factor one used in this paper. A single-factor model cannot, by design, capture the diversification (or lack of it) stemming from an actual correlation between any pair of sectors lower (higher) than that implied by their asset correlations with the single factor.[13] This could result either in an over- or under-estimation of the CVaR, depending on how the asset value correlations are computed and on the combined effect of exposure concentration and the underlying dependency structure within sectors.[14] Also, for the granular portion of the portfolio, the use of the asset correlations prescribed in the IRB approach, without applying the adjustment for size allowed for small and medium enterprises (SMEs, which would require obligor-by-obligor information), is likely to lead to an over-estimation of the CVaR.

To partially address this problem and refine the measure of concentration—within the limits of a single-factor framework—a further measure of CVaR (CVaR-MKMV-CD) is explored for a subset of banks: the shocks to firms' asset values in the non-granular portion of the portfolio (step b) in Section III.), instead of being independently drawn, are drawn from a multi-normal distribution with pairwise correlations given by the partial correlation matrix among firms' asset values (i.e., the matrix of residual correlations after filtering out the common dependence from the systematic factor).[15]

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[12] For the granular part of the portfolio the asset correlations of the IRB formula are used instead, without applying any correction for size (as allowed in the IRB approach for corporate exposures).

[13] For example, if two firms are estimated to have an asset correlation of 25 percent with the systematic factor each, their implied pairwise correlation would be 6.25 percent (square of 25 percent), while in reality they could have a stronger mutual dependence (e.g., because one is a main supplier of the other) or a weaker (or even negative) one (e.g., because they are oligopolistic competitors and one gains from the default of the other).

[14] To clarify the combined effect of exposure concentration and correlation: a portfolio with a particular concentration on a specific sector that has very low (or even negative) correlation with the systematic factor could be better diversified and hence less risky than a more balanced portfolio where all the exposures are more intensely correlated with the systematic factor.

[15] This has been possible only for the firms for which an asset correlation with the systematic factor could be estimated and applies to semi-hypothetical portfolios of Saudi Arabia and UAE banks.

This adjustment allows to better reflect the actual dependence structure between the firms: after all, modeling credit risk dependence through factors—be them one or more—is basically a way around the data limitations and curse of dimensionality that one would face by trying to model portfolio credit risk directly, i.e., by calculating the loss distribution through the joint (multi-normal) distribution of asset values for all the obligors in the portfolio. This would be, of course, not feasible for the whole portfolio; but is doable for the subset of obligors that constitute its non-granular portion, provided time series of their asset values are available to estimate their correlation matrix. We retain the (single) factor underlying structure to still exploit the properties of the ASRF for the granular portion of the portfolio; the common dependence of the non-granular obligors on the systemic factor needs to be "filtered away," by estimating their partial correlation matrix Π,

$$\Pi = \begin{bmatrix} 1 & \pi_{1,2} & \cdots & \pi_{1,m} \\ \pi_{2,1} & 1 & \cdots & \pi_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{m,1} & \pi_{m,2} & \cdots & 1 \end{bmatrix},$$

where the generic element $\pi_{i,j}$ is obtained from the pairwise asset correlation coefficient $\rho_{i,j}$ and the asset correlations with systemic factor w_i and w_j, as

$$\pi_{i,j} = \frac{\rho_{i,j} - w_i w_j}{\sqrt{1-w_i^2}\sqrt{1-w_j^2}}.$$

This represents only a partial solution because it does not address the problem of how to model credit risk dependence in the granular portion of the portfolio, especially by distinguishing between intra-sector and inter-sector correlation.[16]

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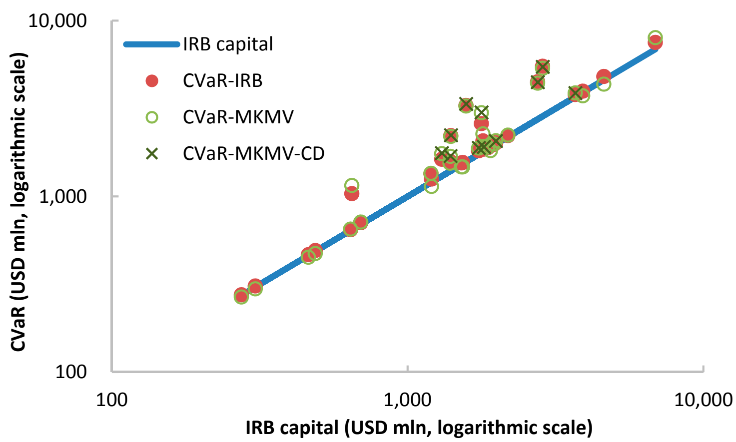
[16] As in the case of firms (see footnote 13), in the ASRF approach intra- and inter-sector correlation between two sectors *h* and *k* are mechanically determined by their asset correlations with the systemic factor, w_h and w_k: in particular, their reciprocal correlation will be given by w_h*w_k, while their intra-sector correlations will be w^2_h and w^2_k, respectively. As for firms, this rules out, inter alia, the possibility of negative correlations between sectors.

Results

First, we compare IRB capital charges and the partial portfolio Credit VaR. In Figure 5 the three alternative capital measures (CVaR-IRB, CVaR-MKMV, CVaR-MKMV-CD) for each semi-hypothetical portfolio are plotted along the 45 degree line representing IRB capital charges. As expected, there is a generally good alignment, with CVaR-IRB consistently lying on or above the IRB line: the results show that the underestimation of credit risk caused by calculating an IRB capital charge without accounting for concentration risk can be sizable: almost 12 percent on average for the 31 banks, with a peak of over 50 percent in one case (i.e. the IRB capital charge would be less than half the CVaR-IRB). The two versions of CVaR-MKMV are also mostly larger than IRB, with some exceptions.

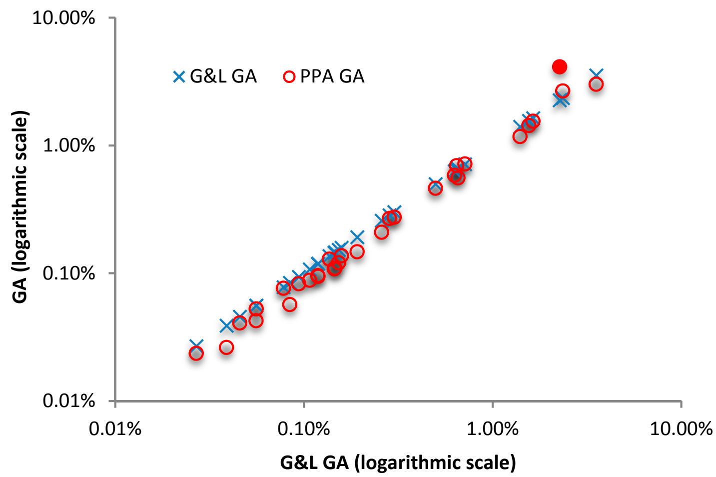
Figure 5. Partial Portfolio Approach for Semi-Hypothetical Portfolios



Next, we analyze and decompose differences between the three CVaR measures and the IRB capital. We start by analyzing the contribution of name concentration: GAs, expressed as a percentage of total portfolio exposure, fall in the range 0.02 to 4.12 percent; the results are quite dispersed, with an average value of 0.62, a median of 0.14 and a standard deviation of 0.99 percent. The range looks very close to that of 0.02 to 3.81 percent reported by Gordy and Lütkebohmert (2013) based on German loan data.

A more direct comparison with Gordy and Lütkebohmert methodology is also done by calculating their GA ("G&L GA") on the semi-hypothetical portfolios (with the same parameterization as adopted in section IV.A) and comparing it with our GA, based on the CVaR-IRB capital measure ("PPA GA"). In Figure 6 the G&L GA is plotted on a 45 degree line.

Figure 6. Granularity Adjustment: Partial Portfolio Approach and Gordy and Lütkebohmert (2013) Methodology



The two measures are generally closely aligned, with the PPA GA lying most of the times slightly below G&L GA. As already said in Section IV.A, our approach could be used to calibrate the parameters in G&L GA approach. However, in the present exercise, calibration would have to be performed separately for each country (as the variance of the systematic factor is likely to differ across countries) and that would have not been feasible, given the limited sample size.

The largest difference between the two GAs (4.12 versus 2.26 percent, marked with the full red dot in Figure 6) is obtained for the portfolio with the highest concentration among all portfolios considered, as measured by HHI: 3.35 percent.

We then investigate the relationship between the partial portfolio GA measure and the HHI, given widespread application of the latter in the calculation of capital adjustments for concentration risk.

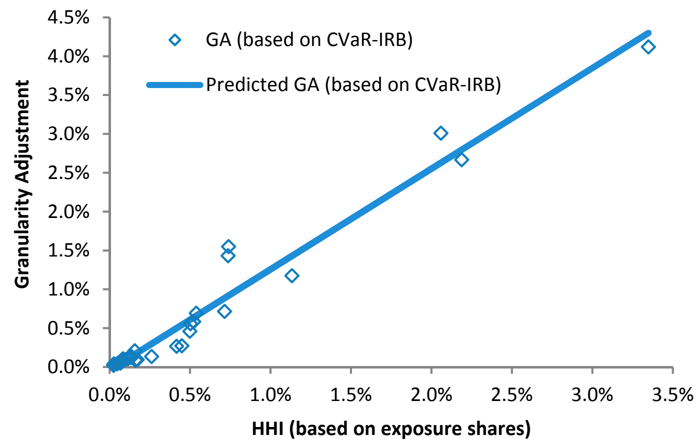
We calculate HHI with respect to shares of exposures, shares of expected losses, and IRB capital charges, always assuming infinitely granular exposures in the granular portion of the portfolio. This translates into calculating and adding up squared shares only for the non-granular portion of the portfolio, with the shares calculated with respect to the overall portfolio, consistent with the assumption underlying the partial portfolio approach.

A linear regression of the PPA GA on the HHI based on exposures shares (Figure 7) gives a very good fit, with a R^2 of 0.96: the GA is linear in HHI with a coefficient of approximately1.3.[17] Importantly, the outlier from Figure 6 is now satisfactorily captured by

[17] The intercept is not statistically significant at a 95 percent confidence level. The use of HHIs calculated on shares of expected losses or IRB capital charges does not lead to improvements in fit.

this relationship. This provides support for the validity of the approach, adopted by a number of supervisory authorities, of creating benchmark models based on a duly calibrated mapping between a bank's HHI and the granularity adjustment.

Figure 7. Granularity Adjustment: Partial Portfolio Approach and HHI

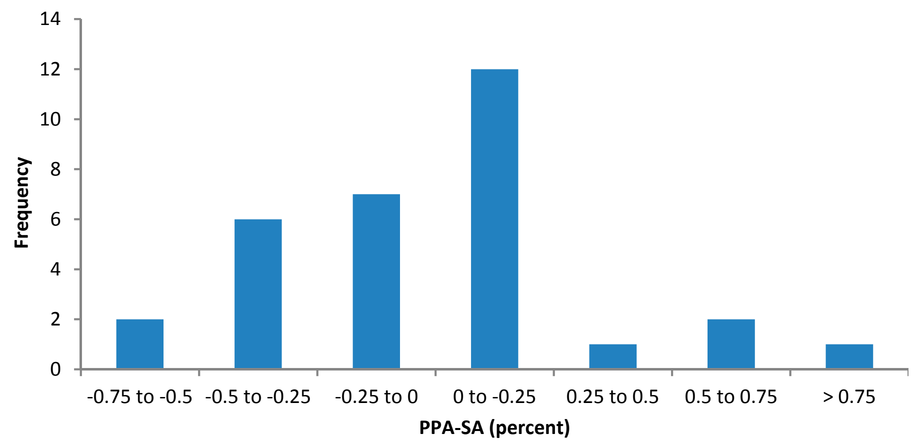


We then analyze the contribution of sector concentration, as measured by the difference between CVaR-MKMV, calculated with firm-by-firm market-based asset correlations, and CVaR-IRB; the difference—that we call "sectoral adjustment" (or PPA-SA)—is expressed again as a percentage of total exposure (Figure 8).

As already explained, unlike for name concentration where real portfolios can only be less granular than the hypothetical infinitely granular one implied by the IRB approach, sector concentration could go in either direction (BCBS, 2006b). Also, while for name concentration there is a clear and well-defined benchmark (the infinitely granular portfolio) that represents a natural floor for Credit VaR, in the case of sector (or geographic) concentration such a benchmark does not really exists; as a consequence, the IRB capital charge—unlike for name concentration—does not have a particular meaning or role to play, and actual Credit VaR can either exceed it or fall below it.

In the case of the semi-hypothetical portfolios analyzed here, sectoral adjustments appear almost equally split between positive and negative ones and their average and median are close to zero.

Figure 8. Distribution of Sectoral Adjustments Across the Semi-Hypothetical Portfolios

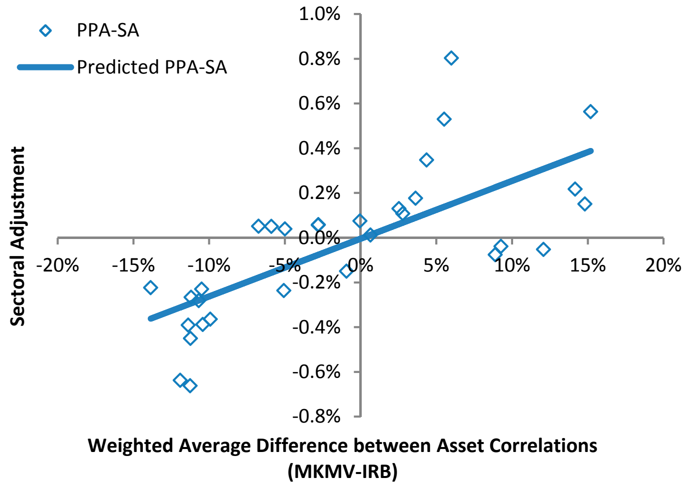


Within the ASRF framework, what can be captured of sectoral concentration is the combined effect of asset correlations larger than those of the IRB approach and the relative weight of sectors where this occurs. We then examine the relationship between the sectoral adjustment and the weighted average of the differences between market-based and IRB-based asset correlations, calculated as

$$\frac{\sum_{i=1}^{m}(w_i^{MKMV} - w_i^{IRB}) * EAD_i}{\sum_{i=1}^{m} EAD_i}.$$

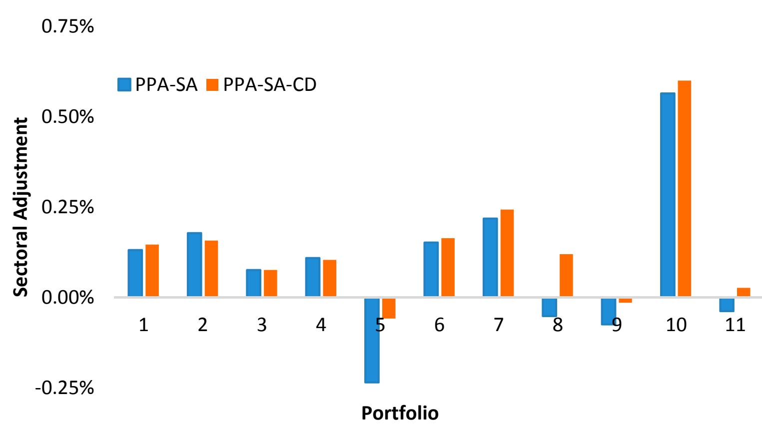
While there is evidence of a clear positive relationship between these two variables (Figure 9), the linear fit looks robust but not particularly strong (R^2 is 0.49): finding a simple, linear relationship for sectoral concentration, amenable to a simple rule with straight calculations also for small and unsophisticated banks, is far less easy than for name concentration.

Figure 9. Sectoral Adjustment and Weighted Average Difference between MKMV and IRB-Based Asset Correlation



Finally, for a limited sample of 11 bank portfolios, we are able to calculate also a sectoral adjustment from the difference between CVaR-MKMV-CD (Credit VaR based on market-based correlations *and* correlated draws for the "non-granular" obligors) and CVaR-IRB; we express it, again, as a percentage of total exposure and label it "PPA-SA-CD." We present the results together with the other sectoral concentration adjustment in Figure 10.

Figure 10. Sectoral Adjustments with and without Correlated Draws in the Simulation



The results show that most of the times the introduction of correlated draws for the non-granular part of the portfolio does not dramatically change the size of the sectoral adjustment, though in some cases the change looks significant (e.g., portfolios 5 and 8) and/or there is a sign reversal (portfolios 8 and 11). Not surprisingly, the largest changes occur for the portfolios with the largest share of non-granular exposures: as explained, the sectoral adjustment is obtained by applying market-based correlations (as opposed to IRB-based) only to these exposures, while keeping the correlation structure fixed for the granular part of the portfolio. It is then legitimate to expect that the introduction of a more realistic dependence structure for the *whole* portfolio could lead to more significant changes, though this goes beyond the aim of this working paper.

V. CONCLUSIONS

This paper addresses a long-standing issue in banking regulation and supervision: how to adjust banks' capital requirements to take into account credit concentration risk, considering that neither of the two Pillar 1 approaches for credit risk (the standardized and internal ratings-based approaches) are meant to capture this source of risk. In the Basel framework credit concentration risk needs to be addressed under Pillar 2, by the banks—which are expected to explain in their internal capital adequacy assessments (ICAAPs) how they decide the amount of capital to set aside against this risk—and by the supervisors—who should challenge banks' assumptions, models and decisions. While some regulators have equipped themselves with different benchmarking tools (either public or undisclosed) that provide an indication of the needed capital add-on, these are generally a result of elaborations and calibrations that are not necessarily within reach of most supervisory authorities.

The most widespread approaches are either model-based or simulation-based: the former are particularly attractive from a regulatory perspective as they allow devising comprehensive rules, derived from fully-fledged models of risk, for banks of any size and complexity to calculate their capital add-ons for concentration risk. However, they cannot easily and flexibly incorporate more advanced features (e.g., dependence of Loss-Given-Default on the systematic factor) and need to be calibrated. That is where the simulation-based methods typically prove helpful, given their flexibility and the possibility to use them to calibrate the former ones. However, while relatively straightforward in application, they are very computer-intensive.

The "partial portfolio" approach proposed in this paper intends to extract the best from these two approaches, by splitting the loan portfolio into a "granular" and a "non-granular" portion and treating the credit risk stemming from the former within the Asymptotic Single Risk Factor framework (the same on which the IRB capital requirement formula is based), while capturing the risk of the latter through fully-fledged Monte Carlo simulations (like in a credit portfolio model). By calculating the difference between the resulting Credit VaR and an IRB capital charge and decomposing the difference, we are able to measure the contributions of name concentration and (within the boundaries of a single-factor framework) that of sector concentration.

As a simulation-based technique, the partial portfolio approach can be easily adjusted to incorporate changing model assumptions, while at the same time it limits the computational burden through the maintenance of the ASRF model assumption for the granular part of the portfolio. It also limits the data requirements. Particularly for the calculation of name concentration capital add-ons, data needs can be reasonably limited: as a minimum only the exposures in the non-granular portion and corresponding probabilities of default, plus the average probabilities of defaults in clusters of the granular portion (defined in terms of sectors, asset classes, rating classes, etc.) are required. Additional data on the dependence structure of the economy (e.g., asset value correlations among firms and among sectors) allow a more accurate calibration of the name-concentration adjustment and are indispensable for sector concentration.

The paper analyzes credit concentration risk from a static point of view, looking at a cross-section of portfolios at a specific date; but the measure proposed can also serve to investigate the evolution of concentration risk through time, as a result of changes both endogenous (changing composition of loan portfolios) and exogenous to the banks (changes in asset value correlations across obligors and sectors): the variability of the dependence structure, in particular, could matter in stressed situations, when correlations typically rise above their long-term levels.

The approach lends itself to be used in bilateral surveillance, as a supplement to traditional solvency stress testing; as a potential area for technical assistance on banking supervision, by helping supervisory authorities to calibrate their own credit concentration benchmarks; and as a policy tool to gauge the degree of concentration risk in different banking systems. Areas for further work include application of the partial portfolio approach to real-world bank portfolios. Such exercises could be conducted e.g. by individual regulators, who have access to more granular, bank-specific data.

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Appendix 1. GCC Banks in Semi-Hypothetical Portfolios Analysis

Country	Banks
Bahrain	Arab Banking Corporation, Ahli United Bank, Bank of Bahrain and Kuwait, Gulf International Bank, Ithmaar Bank
Kuwait	Burgan Bank, Commercial Bank of Kuwait, Gulf Bank of Kuwait, Kuwait Finance House, National Bank of Kuwait
Oman	Bank Dhofar, HSBC Oman, Bank Muscat, Bank Sohar, National Bank of Oman
Qatar	Commercial Bank of Qatar, Doha Bank, Qatar Islamic Bank, Masraf Al Rayan, Qatar National Bank
Saudi Arabia	Al-Rajhi Bank, Saudi British Bank, Banque Saudi Fransi, National Commercial Bank, Riyad Bank, Samba Financial Group
UAE	Abu Dhabi Commercial Bank, Dubai Islamic Bank, Emirates NBD, First Gulf Bank, National Bank of Abu Dhabi