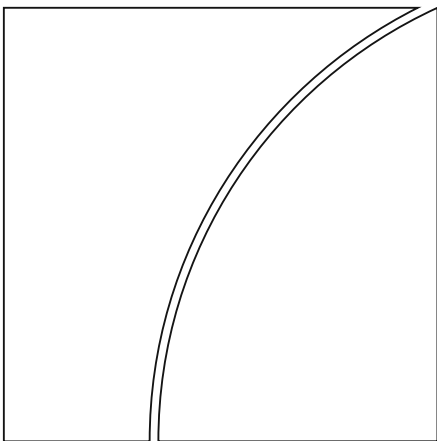


# Basel Committee on Banking Supervision



## Regulatory Consistency Assessment Programme (RCAP)

### Analysis of risk-weighted assets for credit risk in the banking book

July 2013



BANK FOR INTERNATIONAL SETTLEMENTS

This publication is available on the BIS website ([www.bis.org](http://www.bis.org)).

© *Bank for International Settlements 2013. All rights reserved. Brief excerpts may be reproduced or translated provided the source is stated.*

ISBN 92-9131-938-4 (print)

ISBN 92-9197-938-4 (online)

## Contents

Members of the SIG Banking Book Group .....	1
Abbreviations .....	3
Introduction .....	4
Executive summary .....	6
Key findings .....	7
Policy options for consideration .....	8
1. Background .....	11
1.1 Coverage of analysis .....	11
1.2 Terminology .....	11
1.3 Caveats .....	12
2. Review of existing studies .....	13
3. Top-down RWA analysis .....	14
3.1 Structure of the top-down analysis .....	14
3.2 Findings .....	14
4. Portfolio Benchmarking Analysis .....	26
4.1 Structure of the bottom-up portfolio benchmarking exercise .....	26
4.2 Findings .....	30
5. Range of practices .....	41
5.1 Identification of areas of potential differences in practice .....	41
5.2 Exposure at default (EAD) .....	43
5.3 Probability of default (PD) .....	43
5.4 Maturity .....	44
6. On-site discussions with banks .....	46
Annex 1: List of public studies .....	47
Annex 2: CMG data used for the analysis .....	49
Annex 3: Outcome of analysis based on CMG data (30 Jun 2012) .....	50

## Members of the SIG Banking Book Group

### Co-chairs:

Mr Mark Levonian, Office of the Comptroller of the Currency, United States

Mr Nai Seng Wong, Monetary Authority of Singapore

Australia	Mr Guy Eastwood	Australian Prudential Regulation Authority
Belgium	Ms Claire Renoirte	National Bank of Belgium
Brazil	Mr Luis E. Stancato de Souza	Central Bank of Brazil
Canada	Mr Ian Gibb	Office of the Superintendent of Financial Institutions
China	Ms Xiaozhong Liang	China Banking Regulatory Commission
France	Mr Charles Francoise	French Prudential Supervisory Authority
Germany	Mr Stefan Blochwitz	Deutsche Bundesbank
	Mr Michael Bruns	Federal Financial Supervisory Authority
Hong Kong SAR	Mr Yuanfeng Hou	Hong Kong Monetary Authority
India	Mr Ajay Kumar Choudhary	Reserve Bank of India
Italy	Mr Massimo Gangeri	Bank of Italy
Japan	Mr Mitsutoshi Adachi	Bank of Japan
	Mr Taro Asai	Japan Financial Services Authority
Netherlands	Mr Peter De Rijke	Dutch Central Bank
Russia	Mr Vladimir Korovin	Central Bank of Russia
Saudi Arabia	Mr Suliman Aljabrin	Saudi Arabian Monetary Agency
Singapore	Mr Chee Hoe Chan	Monetary Authority of Singapore
South Africa	Ms Liezl Neethling	Reserve Bank of South Africa
Spain	Mr Luis Gonzalez-Mosquera	Bank of Spain
Sweden	Mr Eric Emtander	Swedish Financial Supervisory Authority
Switzerland	Mr Georg Junge	Swiss Financial Market Supervisory Authority
United Kingdom	Mr Jas Ellis	Bank of England
	Mr Kevin Ryan	Bank of England/PRA
United States	Mr Steve Burton	Federal Deposit Insurance Corporation
	Mr Simon Firestone	Federal Reserve Board
	Ms Karen Schneck	Federal Reserve Bank of New York
	Ms Tanya Smith	Office of the Comptroller of the Currency
EU	Mr Paolo Bisio	European Banking Authority
BCBS Secretariat	Mr Christian Schmieder	Secretariat of the Basel Committee on Banking Supervision

**Other contributors:**

Mr Hiroshi Aoki (Japan Financial Services Authority)  
Ms Irina Barakova (Office of the Comptroller of the Currency, United States)  
Mr Edson Bastos (Central Bank of Brazil)  
Mr Boris Benko (Bank of England/PRA)  
Mr Jakub Demski (Bank for International Settlements)  
Mr Gregorio Guidi (Bank of Italy)  
Mr Matthias Huber (Deutsche Bundesbank)  
Mr Hans Kager (Dutch National Bank)  
Ms Yuanyuan Liao (China Banking Regulatory Commission)  
Mr Takayuki Nakata (Japan Financial Services Authority)  
Mr Ajay Palvia (Office of the Comptroller of the Currency, United States)  
Ms Roberta Renz (Office of the Comptroller of the Currency, United States)  
Mr Noel Reynolds (Secretariat of the Basel Committee on Banking Supervision)  
Mr Vinicius Velasco Rondon (Central Bank of Brazil)  
Mr Vincent Sapin (National Bank of Belgium)  
Mr Debashish Sarkar (Federal Reserve Bank of New York)  
Mr Mitch Stengel (Office of the Comptroller of the Currency, United States)  
Ms Annabel F. Y. Tan (Monetary Authority of Singapore)  
Ms Mary Trubin-Barker (Federal Reserve Bank of New York)  
Mr Kapo Yuen (Federal Reserve Bank of New York)

## Abbreviations

A & ROW	Asia/Pacific and Rest of the World
AIRB	Advanced IRB approach
AP	Asia Pacific Region
BCBS	Basel Committee on Banking Supervision
CCF	Credit Conversion Factor
CET1	Common Equity Tier 1 Capital
CMG	Capital Monitoring Group
EAD	Exposure at Default
EL	Expected Loss
EU	Europe (European Union and Switzerland)
FIRB	Foundation IRB approach
G-SIB	Global Systemically Important Bank
HPE	Hypothetical Portfolio Exercise
IRB	Internal Ratings-based Approach (for credit risk)
LGD	Loss Given Default
MRC	Minimum Required Capital
NA	North America Region
RCAP	Regulatory Consistency Assessment Programme
RWA	Risk-weighted assets
SME	Small and Medium-sized Enterprises

# Introduction

Through its Regulatory Consistency Assessment Programme (RCAP), the Basel Committee (Committee) monitors the timely adoption of Basel III regulations by its members, assesses their consistency with the Basel framework and analyses the quality of regulatory outcomes. The RCAP is fundamental to raising the resilience of the global banking system, maintaining market confidence in regulatory ratios, and in providing a level playing field for internationally active banks.

A number of external studies have raised concerns about whether the implementation of the Basel II framework with regard to the internal ratings-based (IRB) approach to credit risk might be uneven. These studies highlight widespread differences in banks' average risk weights. Although there is broad agreement that the observed variations are driven by a mix of differences in underlying risk and differences in banking and supervisory practices, the relative focus on different drivers varies across these studies. These studies also conclude that investigating differences in risk-weighted assets (RWAs) is difficult due to a lack of appropriate and consistent data.

This report presents the findings of the Committee's initial analysis of RWA outcomes for banks that have adopted the IRB approach for credit risk in the banking book. It complements the preliminary findings for RWAs in the trading book published by the Committee in January 2013<sup>1</sup> and the on-going work on RWAs for operational risk.<sup>2</sup> Collectively, these findings on RWA variations will inform other work streams of the Committee including how to increase the robustness of the risk-based capital framework<sup>3</sup> and the fundamental review of prudential requirements for the trading book.<sup>4</sup>

The objective of this analysis was to evaluate drivers of material differences in banking book RWAs calculated using IRB approaches. The analysis addresses the level and variation of risk weights in the banking book at various levels of aggregation, and identifies some of the primary drivers of the variation. The analysis was based on: (i) top-down RWA analysis, with a focus on analysing RWA differences using supervisory data at the country, bank and portfolio levels; and (ii) bottom-up portfolio benchmarking based on a hypothetical portfolio exercise (HPE) comprising a subset of common wholesale obligors to identify practice-based differences in banks' IRB risk parameters. The analysis was overlaid by an assessment of differences in bank and regulatory practices and a list of potentially important practice-based drivers of RWA differences was developed and reviewed.

The study did not attempt to identify an appropriate or acceptable *level* of variation of RWA in the banking book and its findings are sensitive to a number of assumptions.<sup>5</sup> Therefore, the suggestions for policy options are not comprehensive nor do they pre-empt any specific policy measure the Committee could take in the future. Rather, the suggested options serve as a potential direction for future work to be considered by the Committee.

The analysis covered more than 100 major banks around the world based on supervisory data collected by the Committee's Capital Monitoring Group (CMG), as well as data from 32 large international banking groups from 13 jurisdictions for low-default-type wholesale exposures under a

<sup>1</sup> See [www.bis.org/publ/bcbs240.pdf](http://www.bis.org/publ/bcbs240.pdf).

<sup>2</sup> See "Progress report on implementation of the Basel regulatory framework" at [www.bis.org/publ/bcbs247.htm](http://www.bis.org/publ/bcbs247.htm).

<sup>3</sup> See [www.bis.org/speeches/sp130226.pdf](http://www.bis.org/speeches/sp130226.pdf).

<sup>4</sup> See [www.bis.org/publ/bcbs219.pdf](http://www.bis.org/publ/bcbs219.pdf).

<sup>5</sup> See Section 1.3 for details.

HPE. Use of these sources of data available to supervisors addressed to some extent one of the key issues in previous studies,<sup>6</sup> namely a lack of comprehensive and appropriate publicly available data. On-site visits were made to 12 banks that had participated in the HPE to verify the robustness of the off-site analysis and to gain a better understanding of the drivers of observed cross-bank deviations. The study also used surveys to consider differences in the practices of national supervisory authorities, including areas of national discretion permitted in the Basel framework, and differences in the internal estimation practices of banks.

Section 2 reviews the findings and methods of existing analyses of RWA differences. Sections 3 and 4 set out the structure and findings of the top-down RWA analysis and bottom-up HPE. Section 5 describes the work done to assess differences in bank and regulatory practices. Section 6 briefly describes the structure and findings of the on-site visits. The Annexes provide additional detail on the data used in the top-down analysis, as well as a list of some of the many studies conducted by others.

<sup>6</sup> See Section 2 for details.



## Executive summary

This report presents the results of initial analysis by the Committee of variation in risk weights for credit risk in the banking book across major international banks. The focus on credit risk is important, as it constitutes the largest component of risk-weighted assets (RWAs), and a dominant source of overall variations in RWA at the bank level, accounting for 77% of the observed dispersion. In contrast, market risk (at 11%) and operational risk (at 9%) are less important sources of RWA variability.<sup>7</sup>

There is considerable variation across banks in average RWAs for credit risk. In broad terms, the variation is similar to that found for market risk in the trading book.<sup>8</sup> Much of the variation (up to three quarters) is explained by the underlying differences in the risk composition of banks' assets, reflecting differences in risk preferences as intended under the risk-based capital framework. The remaining variation is driven by diversity in both bank and supervisory practices.

A hypothetical portfolio benchmarking exercise (HPE) conducted for a portfolio of matching wholesale (ie sovereign, bank and corporate) credit exposures explicitly investigated "practice-based" differences in risk weights across banks. Translated into capital impact at the bank level, the capital ratios of most banks (22 of the 32 participating banks) would lie within 1 percentage point of a 10% risk-based capital ratio benchmark. However, risk weight variation could cause the reported capital ratios for some outlier banks to vary by as much as 2 percentage points from the benchmark (or 20% in relative terms) in either direction.<sup>9</sup> Notable outliers are evident in each asset class, with the corporate asset class showing the tightest clustering of banks around a central tendency, and the sovereign asset class showing the greatest variation.

The study found a high degree of consistency in banks' assessment of the *relative* riskiness of obligors. That is, there was a high correlation in how banks rank a portfolio of individual borrowers. Differences exist, however, in the *levels* of estimated risk, as expressed in probability of default (PD) and loss given default (LGD), that banks assign. The low-default nature of the assessed portfolios, and the consequent lack of appropriate data for risk parameter estimation, may be one of the factors leading to differences across banks, especially for banks' estimates of LGDs in the sovereign and bank asset classes. A separate survey of bank practices for estimating exposure at default (EAD) also found significant differences.

The report includes a preliminary discussion of potential policy issues raised by the results, and options for future actions by the Committee in its on-going work on the capital framework, Basel III implementation, and supervision.

<sup>7</sup> See section 3.2.2 for details. Variation of RWAs for market risk and operational risk are covered by separate analyses of the Basel Committee. For market risk, see [www.bis.org/publ/bcbs240.pdf](http://www.bis.org/publ/bcbs240.pdf).

<sup>8</sup> This is based on the standard deviation of the variation, and the ratio of maximum to minimum risk weights.

<sup>9</sup> See section 4.2.2 for details.

## Key findings

This study confirms that risk weights for credit risk in the banking book vary significantly across banks, a result that is evident based on confidential supervisory information currently available for global cross-bank comparisons as well as from publicly available data.

Credit risk is the primary component of RWAs and the dominant source of overall RWA variations at the bank level, accounting for 77% of the dispersion. Market risk (at 11%) and operational risk (at 9%) are less important sources of RWA variability.<sup>10</sup> Within the banking book, much of the variability (up to three quarters) in risk weights for credit risk is driven by differences in underlying risk arising from banks' asset composition, ie variation across banks in the relative share of different asset classes and differences in asset composition within asset classes. RWA variation of this type is consistent with the greater risk sensitivity intended by the Basel framework.

However, there are also important *practice-based* drivers that contribute to the remaining RWA variation. Some of these stem from supervisory choices at the national level, due either to discretion permitted under the Basel framework, or deviation in national implementation from Basel standards. These include adjustments made to reflect capital floors and partial use of the standardised approach. Top-down analysis suggests that these account for 3% and 5% of overall RWA variability, respectively.<sup>11</sup>

The differences in practices also result from banks' choices under the IRB framework, ie varying IRB approaches used by banks,<sup>12</sup> conservative adjustments to IRB parameter estimates, and differences in banks' modelling choices (for example choice of reference data, or methodological differences, such as PD master scales, definition of default, adjustment for cyclical effects, and the treatment of low-default portfolios).<sup>13</sup> In some cases, variations may also reflect differences in interpretation of the Basel framework.

The bottom-up portfolio benchmarking exercise (the hypothetical portfolio exercise, or HPE),<sup>14</sup> under which banks were asked to evaluate the risk of a common set of (largely low-default) wholesale obligors and exposures, revealed notable dispersion in the estimates of PD and LGD assigned to the same exposures.<sup>15</sup> The three wholesale asset classes covered by the HPE analysis (sovereign, bank, and corporate) account on average for about 40% of participating banks' total credit RWAs.<sup>16</sup> A rough translation of the implied risk weight variations into potential impact on banks' capital ratios suggests that the impact could be material; at the extremes, capital ratios could vary by as much as 1.5 to 2 percentage points (or 15 to 20% in relative terms) in either direction around the 10% benchmark used

<sup>10</sup> See section 3.2.2 for details. Variation of RWAs for market risk and operational risk are covered by separate analyses of the Basel Committee. For market risk see [www.bis.org/publ/bcbs240.pdf](http://www.bis.org/publ/bcbs240.pdf).

<sup>11</sup> See sections 3.2.5 for details. Other practice-based drivers whose effects were roughly quantified include the differential treatments of defaulted exposures and differential treatments of securitisation exposures, although the analysis indicates that these drivers tend to reduce observed RWA variability by lowering overall average risk weights (see section 3.2.5 for details).

<sup>12</sup> Foundation IRB or Advanced IRB.

<sup>13</sup> Some of these choices may also reflect supervisory decisions.

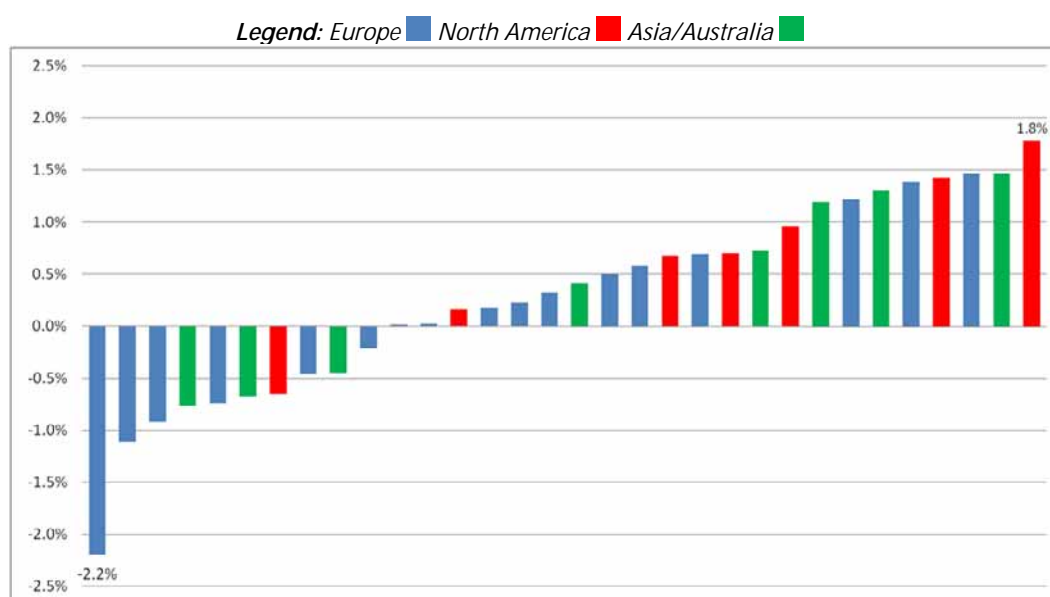
<sup>14</sup> The HPE assessed the impact of practice-based differences on assigned IRB risk weights for a sample portfolio drawn from the wholesale asset classes across 32 large international banking groups.

<sup>15</sup> The use of the same exposures should largely eliminate risk-based differences, leaving only bank and supervisory practice-based variation.

<sup>16</sup> The HPE covered only portions of each of these asset classes, primarily central government sovereigns, globally significant banks and large corporate obligors.

for this study. However, most of the banks (22 of the 32 participating banks) lie within one percentage point of that benchmark (see Chart 1 below).<sup>17</sup>

Chart 1: Impact of Risk Weight variation on capital ratios



Change from 10% capital ratio if individual bank risk weights from the HPE are adjusted to the median from the sample. Each bar represents one bank. The chart is based on the assumption that variations observed at each bank for the hypothetical portfolios are representative for the entire sovereign, bank, and corporate portfolios of the bank and are adjusted accordingly. No other adjustments are made to RWA or capital.

LGD estimation appears to be a significant source of cross-bank differences in RWAs under the Advanced IRB. Practices vary due in part to the less-advanced stage of development of LGD modelling and to a lack of data of sufficient quality, quantity, and relevance, especially for low-default portfolios. Similar observations were found for EAD estimation based on separate analysis that drew on survey information.

The deviations across banks in the HPE approximately correspond to those found in the similar exercise for market risk in the trading book.<sup>18</sup> Most of the analysis does not find notable or distinctive regional patterns in the results.

## Policy options for consideration

While most RWA differences can be explained by variations in underlying risk, and are hence desirable, there is a material amount of dispersion due to differences in practices.<sup>19</sup> Some amount of variation would be expected in any regime based on internal models and especially for low-default portfolios. While the initial findings of this report will benefit from further analysis that the Committee plans to

<sup>17</sup> See section 4.2.2 for details.

<sup>18</sup> Based on the standard deviation of the variation and the ratio of maximum to minimum risk weights.

<sup>19</sup> It should be noted that not all practice-based differences are “undesirable”, given that different modelling would result in different outcomes, but different practices should not produce material differences.

undertake, they do point towards some areas for policy action, future work, or a combination of the two if narrowing of the variation in outcomes is to be pursued.

The Committee is conscious of the need to ensure that the capital framework retains its risk sensitivity, while at the same time promoting improved comparability of regulatory capital calculations by banks. There are important trade-offs between potential measures to harmonise practices on the one hand and some of the other objectives of the Basel framework on the other, such as providing flexibility to accommodate differences in risk appetite and local practices, and providing incentives for risk management improvements to achieve greater accuracy in risk measurement and capital calculations. In addition, from a financial stability perspective, some diversity in risk management practices is desirable to avoid uni-directional behaviour that could become a source of instability.

The short-term policy options that the Committee will consider include enhanced disclosure, additional guidance, and possible clarifications of the Basel framework. These options could be built on in the on-going work on enhanced disclosure by the Committee's Working Group on Disclosure, and the RCAP assessment process. The RCAP is dealing with country-specific consistency vis-à-vis the Basel framework, and helping identify potential areas of different interpretation that need clarification or refinement in the regulatory framework. In addition, national supervisors will undertake supervisory follow-up with specific banks.

Over the medium term, the Committee will examine the potential to further harmonise national implementation requirements and to put constraints on IRB parameter estimates. This policy work would also benefit from additional top-down analyses based on better data, such as more granular information on the types of exposures within bank portfolios and information on credit risk mitigation. It may also be valuable to examine how cross-bank differences in RWAs vary over time as banks transition from Basel I to Basel II and then to Basel III.

### Enhanced disclosures by banks

Enhanced Pillar 3 disclosures by banks could foster greater market discipline and avoid misperceptions as to the level and causes of RWA variations. Valuable areas for enhanced disclosure include more granular information on asset class mix, internal risk grade distribution and associated risk parameter estimates, the share of defaulted exposures, information about the major sources of changes in RWAs over reporting periods, information about choices of credit-risk approaches, capital floor adjustments, and other aspects of regulatory capital calculations that might vary across banks. Use of standardised definitions and templates could support greater consistency and comparability of disclosures. The proposals parallel certain recommendations of the Financial Stability Board's Enhanced Disclosure Task Force, as contained in the recent report of that task force.

### Additional guidance on aspects of the Basel framework

Some drivers of RWA variation are the result of differences in interpretation and/or practices within areas that are left unspecified or less than fully specified within the capital framework. Examples include adjustment of IRB parameter estimates for conservatism or cyclical effects, and use of external data, particularly for low-default portfolios. In some areas, it may be appropriate for the Committee to provide additional guidance to reduce or eliminate undesirable variation attributable to such differences.

### Harmonisation of national implementation requirements

Some of the drivers of variation in RWA stem from aspects of the Basel framework itself, or from differences in its implementation in various jurisdictions. Examples where additional clarity could be provided and contribute substantially to reducing undesirable variation in RWAs include capital floor

adjustments, partial use of the standardised approach, definition of default, treatment of defaulted exposures, exemptions from the one-year maturity floor, and requirements related to estimation of IRB parameters. Many of these drivers could be addressed through clarification of the framework, through efforts to harmonise national implementation requirements, or through review of the continued relevance of various aspects of national discretion.

### Constraints on IRB parameter estimates

A final option could be to limit the flexibility of the advanced approaches. For example, supervisory benchmarks for risk parameters could be created from the data collected through this study and similar future work. Creation of such benchmarks could fill a valuable niche, especially for low-default portfolios, creating reference points for supervisors and banks. Benchmarks might include representative PD estimates for particular rating grades or for other indicators of credit quality, representative LGD estimates for various types of exposures or representative CCF estimates based on observed bank practices. Any benchmarks created would need to be communicated with care to avoid making them appear to be either regulatory requirements or “safe harbour” estimates, and to ensure that any potential reduction of variation does not come at the expense of a general decline in the level of RWAs. Other alternatives could include more explicit constraints, such as the creation of floors for certain parameters (such as LGD), or even fixed values of such parameters.

# 1. Background

## 1.1 Coverage of analysis

The analysis covered the following areas:

*Top-down RWA analysis:* The focus was on analysing RWA differences using supervisory data at the country, bank and portfolio levels collected by the Committee's CMG.

*Bottom-up portfolio benchmarking:* An HPE benchmarking exercise was conducted using a test portfolio comprising a subset of common wholesale obligors to identify differences in banks' IRB risk parameters.

*Range of practices:* To overlay the analytical work with an assessment of differences in bank and regulatory practices, a list of potentially important practice-based drivers of RWA differences was developed and thematic reviews of selected risk measures were conducted.

*On-site visits:* On-site visits were made to 12 banks that participated in the bottom-up HPE to verify the robustness of the off-site analysis and to gain a better understanding of the drivers of observed cross-bank deviations.

## 1.2 Terminology

To facilitate understanding and comparison, this report uses the following terminology to describe the drivers of RWA differences:

- *"Risk-based"* drivers are those that produce or reflect differences in underlying risk at the exposure/portfolio level, such as differences in business and risk management strategies, product and customer mix, risk characteristics of banks' exposures, and market and economic conditions. Legal frameworks across jurisdictions (bankruptcy laws, recovery processes, access to collateral etc) can also affect default rates, draw-down behaviour and recovery outcomes, thereby contributing to differences in underlying risk profiles. Differences in RWAs resulting from such drivers reflect the desired outcome of the Basel framework, which was to align capital adequacy requirements more closely with banks' underlying risk profiles.
- *"Practice-based"* drivers are a diverse group of drivers stemming from differences in bank practices and the regulatory environment that relate to risk measurement for capital purposes. These in turn can be split into two broad components:
  - The relevant regulatory environments that banks face in this respect can vary: potentially, there can be differences between jurisdictions in relevant supervisory practices, in relevant implementing laws and regulations, in supervisors' interpretations of the Basel framework, and in accounting standards.
  - In addition, banks may have made different methodological choices regarding risk rating, segmentation, quantification, and validation; and have interpreted the rules implementing the Basel standards in various ways.

Note that practice-based drivers can also be subdivided into those that are specifically provided for under the Basel framework (eg IRB rollout, national discretions), and others that arise more from differences in interpretation of standards in the framework or from specific practices such as those related to calibration of risk parameters.

### 1.3 Caveats

The availability of suitable data is a key challenge when analysing RWA variation. While the CMG dataset provides broad coverage across many banks and jurisdictions, it is not sufficiently granular to support more detailed analyses needed to identify particular drivers.<sup>20</sup> To overcome such data constraints, some of the analyses rely on a number of simplifying assumptions.

Moreover, the CMG data collection started only in 2008 (coinciding with the introduction of Basel II), which may not be adequate for time-series analyses through a full business cycle. Similarly, the bottom-up portfolio benchmarking exercise collected data as of June 2012 only. As a result, many of the analyses in this report represent only a cross-sectional snapshot of RWA variation across banks at June 2012.<sup>21</sup> Indeed, during the on-site visits, some banks revealed that they were changing or had changed their internal models subsequent to the as-of date for the HPE data. Some of these changes were in response to supervisory follow-up from the banks' home supervisors. Further, the analyses focus on Pillar 1 capital requirements and so do not take into account Pillar 2 treatments, which may vary across jurisdictions and may offset observed Pillar 1 variation to some extent.

A significant challenge for this work is the fact that "true" levels of underlying risk are unknown. As a result, in many cases, the analysis is able to identify differences in RWA across banks, but cannot determine definitively whether these differences correspond to differences in underlying risk.<sup>22</sup>

Taken together, these caveats suggest that a degree of caution should be exercised when interpreting the results of this analysis.

<sup>20</sup> Such as credit conversion factors, effects of credit risk mitigation, differentiation between temporary and permanent partial use, differences in exposure types beyond broad asset classes, differentiation between lending and counterparty credit risk exposures, information by PD-bands, and impact of geographical mix.

<sup>21</sup> For example, the analyses would not reflect any changes to internal models made after the date of the data collection.

<sup>22</sup> Two banks may have identical RWAs, both of which are based on faulty estimates, or they may have reported very different RWAs for superficially similar portfolios that are in fact different in risk (eg due to different credit risk mitigation). An additional complication is that risk depends in part on risk management practices at the level of the bank or portfolio (eg collection practices for problem loans) that are difficult or impossible to identify and assess based on available data.

## 2. Review of existing studies

The Committee reviewed a wide range of existing analyses of RWAs across banks and jurisdictions to assess methodologies and identify possible drivers of RWA differences (Annex 1).<sup>23</sup> The various studies highlighted many potential drivers; as with the public studies for market risk, the studies for the banking book do not provide conclusive evidence regarding the specific causes of RWA differences. Rather, most analyses suggest that RWA differences are driven by both risk-based and practice-based factors, with varying relative contributions.<sup>24</sup>

Most studies suggest that at least some of the variation in RWAs could be attributable to practice-based drivers. For example, several studies from the regulatory community identified model calibration (particularly PD and LGD estimation) as a driver of RWA variation. On the other hand, external analysts paid more attention to differences in the application of supervisory principles, with regulatory and accounting approaches being frequently cited as reasons for differences in RWA measurement.

The review also highlighted important lessons for the Committee's own analytical work as well as potential recommendations:

- There is a need to carry out both top-down and bottom-up analyses while recognising the limitations of each method.
- Better analysis can be conducted by using more complete (including non-public) data sources, and analysis could be improved further by collecting new, comparable and better data directly from selected banks.
- An assessment of differences in specific practices by banks and national supervisors and from other sources such as accounting standards, can help better identify and understand ultimate drivers of RWA differences.

<sup>23</sup> Twenty-eight studies from 21 organisations were reviewed (Annex 1). These included research prepared by Committee member organisations as well as by external analysts.

<sup>24</sup> Some differences were evident between studies conducted by regulators and studies conducted by other analysts. Some of those differences in emphasis between official sector and private sector studies derive from data availability, particularly granular and comparable supervisory data that may not be available to the private sector as banks are not required to publish such data under Pillar 3 or, if they do, do not do so in a consistent way.



### 3. Top-down RWA analysis

#### 3.1 Structure of the top-down analysis

The top-down analysis was conducted using supervisory data collected semi-annually by the CMG as part of on-going capital monitoring since end-June 2008, as further outlined in Annex 2. The results presented below are based on an analysis of the CMG data as of June 2012 unless otherwise stated.

The top-down analysis included the following key aspects:

- An identification of the material risk classes (eg credit risk, market risk, and operational risk) and other factors (eg capital floor adjustments, eligible reserve shortfalls or excesses relative to expected losses, and portfolio-related capital deductions that are built into the Basel framework) that contribute to the level and variation of capital requirements in general and credit risk RWA in the banking book in particular, across both banks and jurisdictions.
- Portfolio analytics that explore the influence of differences in asset class mix, and differences in EAD-weighted IRB risk parameter estimates in explaining the dispersion that exists in banking book risk weights across banks.
- Analyses of certain drivers believed to play a material role in RWA dispersion, including partial use of the standardised approach, use of the foundation IRB (FIRB) or advanced IRB (AIRB) approach, the treatment of defaulted exposures, and the treatment of securitisation exposures.
- An analysis of the relationship between RWA and proxies for underlying risk.

#### 3.2 Findings

##### 3.2.1 RWA variability

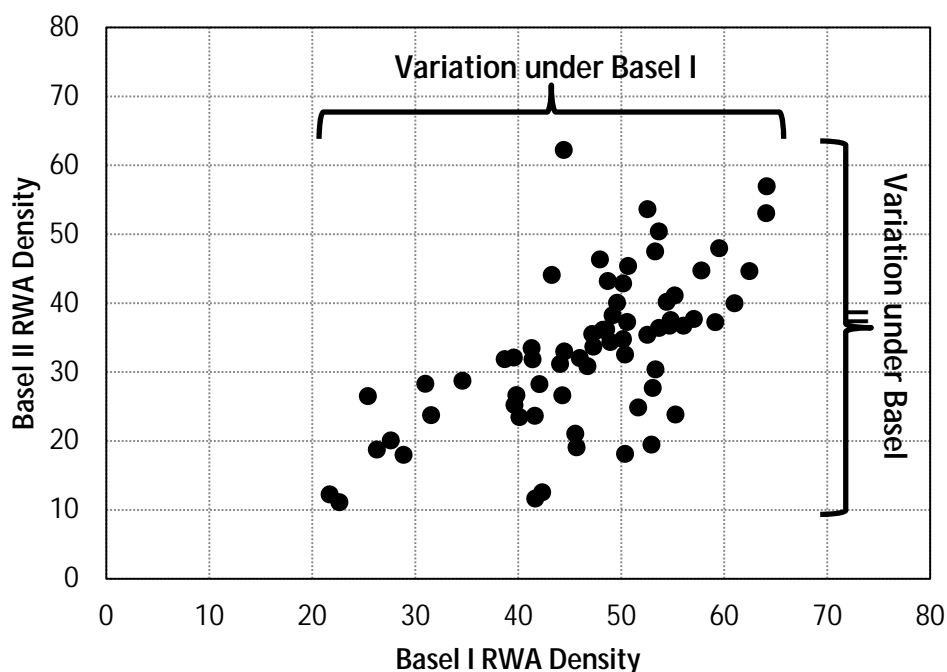
Risk weights for credit risk in the banking book vary significantly across banks; under both Basel I and Basel II (see Chart 2). Based on data for 67 banks, the average risk weight for individual banks' exposures varied between 11% and 62% under Basel II, compared with between 22% and 64% under Basel I.

The variability in average risk weights under Basel II was found to be higher than under Basel I (see Table 1, coefficient of variation). This should be expected, since Basel II is intended to be more risk-sensitive, and therefore should be more reflective of variability in the riskiness of banks' credit portfolios. However, it is worth noting that risk weight variations existed even under Basel I. Since Basel I prescribed standard risk weights for broad asset classes, such risk weight variations would generally be reflective of differences in asset class mix. The significant correlations<sup>25</sup> between Basel I and Basel II risk weight densities as indicated in Table 1 suggest that a substantial portion of the risk weight variations under Basel II could similarly be attributed to asset class mix (see section 3.2.4).<sup>26</sup>

<sup>25</sup> In terms of both the absolute levels of banks' risk weights and the rank ordering of banks by risk weights.

<sup>26</sup> The Committee also evaluated the extent to which Basel II risk measures are correlated with other risk measures. Further information is provided in Annex 3.

Chart 2: Dispersion of credit RWA density under Basel I vs Basel II



The chart compares the credit-risk RWA densities (essentially, average risk weights) under Basel I and II for 67 CMG banks as of June 2012, ie for the universe of CMG data where Basel I information was available (about two thirds of the CMG banks). “RWA density” is RWA per unit of exposure, calculated as the ratio of credit RWA to EAD.

Comparison of variability in Banking Book: RWA density under Basel I and Basel II, and correlations between Basel I and Basel II<sup>27</sup>

Table 1

	Basel I	Basel II
Coefficient of variation, Std Dev/Mean	0.24	0.34
Pearson's coefficient of correlation	0.70	
Spearman's coefficient of correlation	0.66	

### 3.2.2 Material risk classes

Credit risk is the dominant driver of capital requirements at the bank level (for the universe of 102 CMG banks), accounting for around two thirds of RWAs<sup>28</sup> (Table 2). Other RWA components are generally less

<sup>27</sup> Based on an analysis of 67 of the 102 banks in the Committee's dataset for which Basel I banking book RWAs can be inferred from data as well as data from the ongoing Basel III Monitoring Quantitative Impact Study.

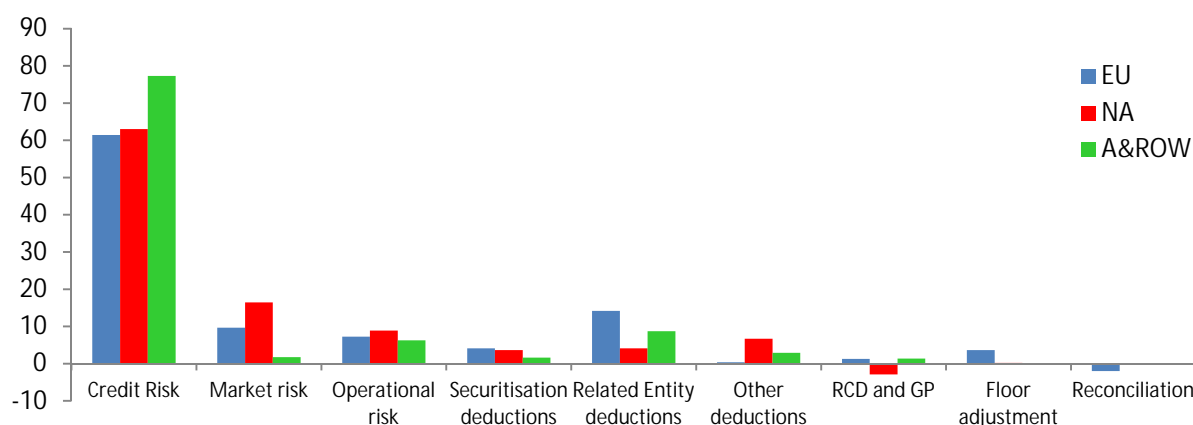
<sup>28</sup> In section 3.2.2, RWAs are proxied by minimum required capital (MRC). MRC is calculated as the sum of 8% times RWAs, plus deductions from capital to include shortfalls in provisions relative to expected losses (excess provisions would reduce MRC), plus capital requirements pertaining to any floor adjustment.

material, each making up no more than 10%. Chart 3 shows that the RWA shares of different asset classes are broadly similar across geographical regions, with a few minor differences:

- Credit Risk RWAs have the highest share in Asia & Rest of the World.
- Market Risk RWAs tends to be relatively higher in North America than in other areas.
- Capital floor adjustments are material only in Europe.
- Provision shortfalls to expected losses (EL) contribute to RWA in Asia & Rest of the World and Europe; North America shows provision excesses relative to ELs.

Share of RWA across risk types (%)						Table 2
	Mean	Median	Minimum	25th percentile	75th percentile	Maximum
<b>Credit Risk</b>	<b>64.0</b>	<b>71.1</b>	<b>19.5</b>	<b>56.1</b>	<b>81.4</b>	<b>97.4</b>
Market risk	9.5	2.3	0.0	0.6	7.0	43.1
Operational risk	7.3	6.6	1.7	5.3	8.6	79.6
Securitisation deductions	3.6	0.2	0.0	0.0	2.3	20.5
Related entity deductions	10.9	2.3	0.0	0.0	6.9	48.2
Other deductions	2.2	0.0	0.0	0.0	1.2	21.4
Regulatory calculation differences and general provisions	0.4	0.8	0.0	0.0	4.0	16.9
Floor adjustment	2.2	0.0	0.0	0.0	1.2	71.4
Reconciliation	0	0.0	0.0	0.0	0.0	0.9

Chart 3: Share of RWA by risk type and geographical region



The chart shows the share of RWAs accounted for by the different risk types for banks in different geographical regions. For example, credit risk accounted for around 60% of RWAs for EU and North American (NA) banks but close to 80% of RWAs for banks in Asia and Rest of the World (A&ROW).

The dominance of credit risk RWAs within overall RWAs is evident in a decomposition of RWA variability by risk type<sup>29</sup>, which indicates that credit risk contributes the bulk of the variability. Market risk, operational risk and capital floor adjustments make a much smaller contribution (Table 3).

Decomposition analysis of RWA variability by risk type		Table 3
Risk type	Variance share (%)	
<b>Credit Risk</b>	<b>77</b>	
Market Risk	11	
Operational Risk	9	
Capital Floor Adjustments	3	

### 3.2.3 Material credit risk categories

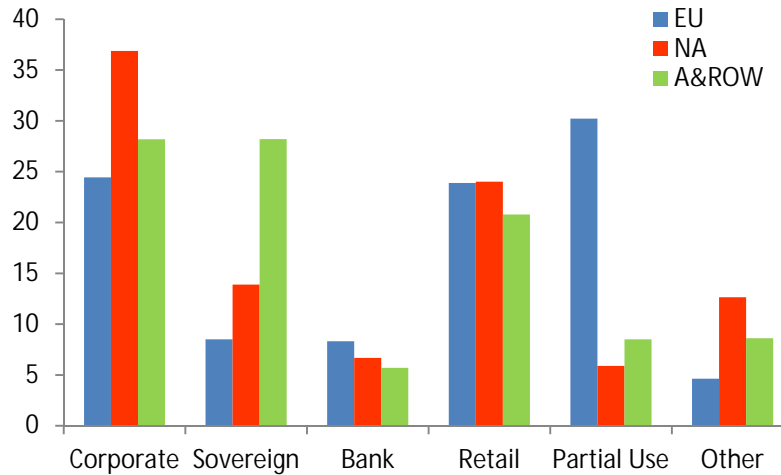
Within the credit risk category, corporate and retail exposures are the largest, accounting for 27% and 23% respectively of credit risk exposures (EAD) (Annex 3, Table 1). There are, however, some regional variations, with sovereign exposures being more significant in Asia and Rest of the World while partial use (ie use of the Standardised Approach by IRB banks)<sup>30</sup> is more prevalent in Europe (Chart 4). In terms of RWAs, corporate credit accounts for 37% of the total RWAs in the banking book, partial use 27%,

<sup>29</sup> This analysis is based on actual RWAs (not MRC). The outcome is derived by: (i) regressing overall variations in RWAs against the components of minimum required capital in Table 2; (ii) multiplying the significant coefficients by the RWA share of the respective components; and (iii) dividing the result for each component by the sum of all the components to derive the contribution share of each component.

<sup>30</sup> See also the discussion on partial use in section 3.2.5.

retail credit 18%, bank credit 4%, sovereign credit 1% and other portfolios (other assets, securitisations, equity, funds, receivables, and related entities) for 12%.

Chart 4: Share of credit exposures (EAD) by asset class and geographical region



The chart shows the share of EAD accounted for by the different asset classes for banks in different geographical regions. For example, corporate exposures accounted for around 25% of EAD for EU banks, more than 35% of EAD for NA banks and slightly less than 30% of EAD for banks in A&ROW. Partial use exposures are characterised as a separate asset class under the CMG data template.

The corporate and retail asset classes also show the greatest absolute variation in risk weights across banks and jurisdictions. Bank and sovereign exposures are less significant contributors to RWA variations because of their lower absolute risk weights, although relative variability in risk weights within these asset classes is significant (Table 4).

Risk Weight distribution within asset classes (%)							Table 4
	Mean	Median	Minimum	25th Percentile	75th Percentile	Maximum	No. of banks
<b>Corporate</b>	<b>48</b>	<b>56</b>	<b>2</b>	<b>44</b>	<b>64</b>	<b>86</b>	<b>88</b>
<b>Retail</b>	<b>28</b>	<b>21</b>	<b>7</b>	<b>16</b>	<b>29</b>	<b>101</b>	<b>89</b>
Bank	18	17	1	14	25	46	77
Sovereign	3	5	0	2	8	100	67

Combining the effects of asset class size and risk weight variability,<sup>31</sup> the corporate and retail asset classes are the most important contributors to RWA variations, accounting for around three-quarters of the overall variation attributable to credit risk (Table 5).

<sup>31</sup> This was computed as follows: (i) Calculate the variance of RWA density for each portfolio; call this  $v_i$ . (ii) Calculate the exposure shares for each portfolio,  $a_i$ . (iii) The variance of the overall density is  $\text{Var } X = a_1^2 v_1^2 + a_2^2 v_2^2 + \dots + a_i^2 v_i^2$ ; the share for portfolio 1 is  $a_1^2 v_1^2$  over the total.

Decomposition analysis of RWA variability by asset class

Table 5

Asset class	Variance share (%)
<b>Corporate</b>	<b>42</b>
<b>Retail</b>	<b>34</b>
Sovereign	10
Securitisations	7
Other asset classes	7

### 3.2.4 Impact of asset class mix and within-asset-class composition

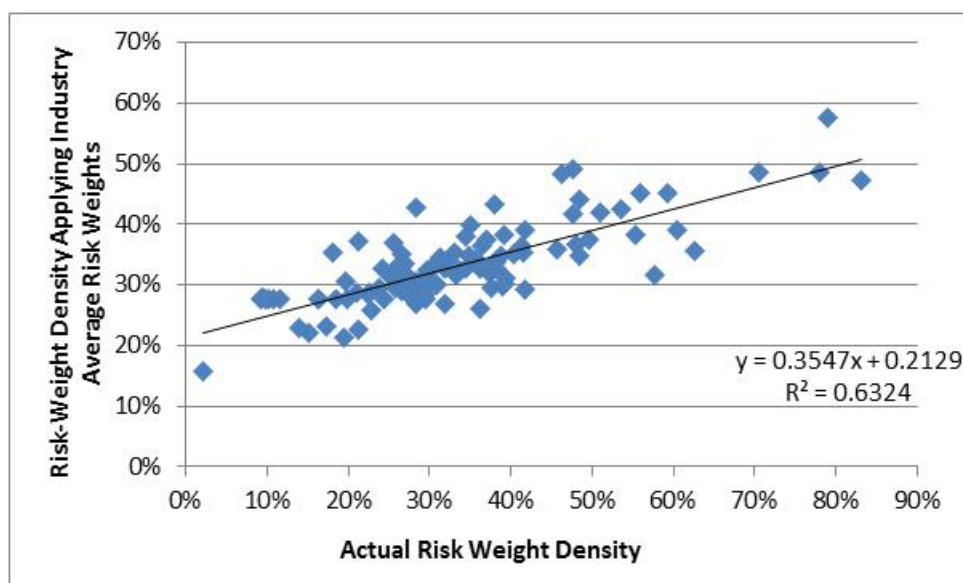
To assess how differences in asset class mix across banks may impact RWA variability, the actual average risk weight of each bank was compared against a counterfactual risk weight calculated by applying the industry average risk weights for each IRB asset class<sup>32</sup> to the bank's actual exposures. Since the counterfactuals for all banks are based on the same industry average risk weights for each of the specific asset classes, the differences in the counterfactuals depend only on differences in asset class mix. The correlation between the counterfactuals and the actual risk weights is indicative of how much of the variation in risk weights can be explained by asset class mix alone (Chart 5).

The analysis found a correlation of more than 60%.<sup>33</sup> This suggests that a major portion of the variation in risk weights across banks reflects differences in underlying risk due simply to varying asset class mix. The remaining dispersion would be due to different risk weights within asset classes – from either differences in actual risk (risk-based) or its measurement (practice-based).

<sup>32</sup> The nine asset classes in the CMG dataset are corporate, retail, sovereign, bank, equity, securitisation, receivables, related entities, and other assets. Partial use exposures are not included in this analysis.

<sup>33</sup> Complementary analysis based on the standard deviation of RWA densities for the same counterfactual analysis suggests that about half of the variation is driven by asset class mix.

Chart 5: Risk Weight Density applying actual Risk Weights  
vs. industry average Risk Weights



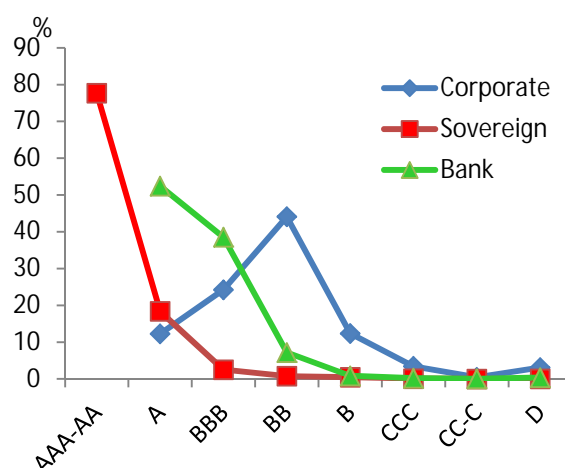
The chart shows a scatter plot with each point representing a bank, with the horizontal axis showing the bank's actual risk weight density and the vertical axis showing its counterfactual risk weight density calculated using the industry average risk weight for each asset class. If every bank assigns the industry average risk weight for each asset class to its own exposures, then the resulting variation in risk weight density across banks would be driven solely by asset class mix. Such a situation would be represented by banks having counterfactual risk weights equal to their actual risk weights, ie banks would align along a 45° line. If all banks instead align along a horizontal line, the implication would be that asset class mix does not drive RWA variation.

Chart 6 illustrates the fact that the general riskiness of the asset classes differs for the various wholesale asset classes, where exposures to sovereigns are concentrated in the lowest risk band (AAA–AA), bank exposures in the A band and corporate exposures in the BB band.<sup>34</sup> The average risk weights associated with these asset classes follow the same order, with the lowest risk weights for sovereign exposures and corporate exposures exhibiting higher risk weights.

Deviation from these average risk weight distributions within asset classes constitutes the other important risk-based driver for RWA deviations. Tentative estimates of the relative contribution of risk-based and practice-based deviations within asset classes suggest that both types of drivers matter, with perhaps equal impact.

<sup>34</sup> The analysis was performed using 30 Jun 2012 data for a sub-sample of CMG banks for which data at the level of PD-bands is available; 56 banks for the sovereign asset class, 66 banks for the bank asset class and 76 banks for the corporate asset class.

Chart 6: Mean exposure shares by rating grade (%)



The chart shows the share of exposures for the different asset classes in each implied external rating grade (ie with banks' PD estimates mapped to a single master scale). For example, close to 80% of sovereign exposures were rated AAA-AA.

### 3.2.5 Practice-based differences

#### *Capital floor adjustments*

The Committee investigated specific practice-based drivers for variation in risk weights. As shown above, a variance decomposition of RWA variability suggests that capital floor adjustments tied to Basel I capital requirements contribute around 3% of overall RWA variations. There are varying rules-based practices across jurisdictions pertaining to the application of capital floor adjustments. Several jurisdictions no longer require such floors. Among jurisdictions that continue to apply floors, there are significant differences in both the level of the floor applied (ranges from 80 to 100%) and how the floor is calculated.

For the 16 CMG banks that are currently constrained by capital floors, the extent to which capital floor adjustments add to RWA varies widely from almost no increase to increases of nearly 80%. For these banks, the prevalence of retail exposures (which tend to attract lower Basel II risk weights vis-à-vis Basel I) helps explain around 50% of the variation in capital floor adjustments (ie banks with larger retail portfolios tend to require larger capital floor adjustments). Nevertheless, the varying rules for capital floor adjustments result in differences in capital requirements and RWA across banks that are not wholly based on differences in risk or asset class mix.

#### *Partial use*

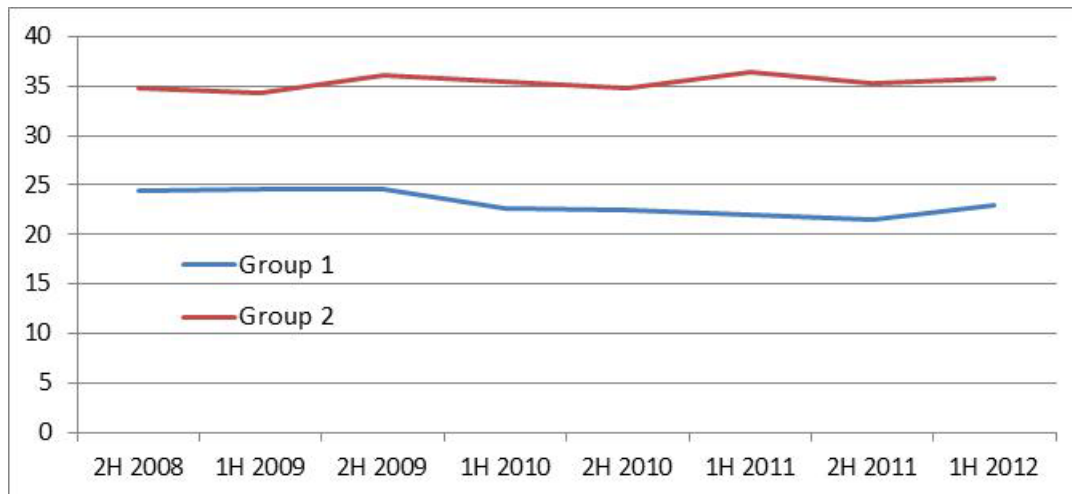
Another material practice-based driver is the partial use of the standardised approach for credit risk by IRB banks. Partial use has been consistently significant since the introduction of the Basel II framework, accounting for more than 20% of the exposures for Group 1 banks and 35% for Group 2 banks (Chart 7).<sup>35</sup> RWAs for partial use exposures are determined by standard risk weights as opposed to IRB exposures where RWAs are determined by IRB parameters.

<sup>35</sup> Group 1 banks are those that have Tier 1 capital in excess of €3 billion and are internationally active. All other banks are considered Group 2 banks.



There are two types of partial use: *temporary* and *permanent*. Temporary partial use is applied in the initial years of IRB implementation as banks transition their portfolios to the IRB approach. As the name implies, the proportion of exposures under temporary partial use is generally expected to decline over time for any given bank. Permanent partial use is applied in some jurisdictions to sovereign, bank and non-material exposures. The proportion of exposures represented by permanent partial use is expected to remain broadly constant over time. The CMG dataset does not distinguish between these two types of partial use.

Chart 7: Share of partial use (%)



The top-down analysis (which extrapolates banks' IRB parameters to partial use exposure) suggests that greater partial use of the standardised approach leads to higher corporate and retail risk weights; the corollary is that greater use of the IRB approach produces, on average, lower corporate and retail risk weights than under the standardised approach (Annex 3, Table 6). In contrast, the correlation between the share of partial use and the risk weight for the sovereign asset class is weakly negative, suggesting that higher partial use may contribute to lower sovereign risk weights, but only very slightly. No clear relationship between partial use shares and risk weights for the bank asset class is observed.

#### *FIRB vs AIRB*

The Committee further considered whether RWA differences are associated with IRB banks' choice between FIRB and AIRB. The analysis indicates that AIRB banks tend to have lower risk weights than FIRB banks for corporate exposures on average (Table 8). Much of this difference can be explained by the lower LGDs AIRB banks assign to corporate exposures as compared with FIRB banks – 33% versus 40% on average. The difference could also be partially explained by CCF estimates for corporate exposures, which are typically below the 75% CCF specified under FIRB.<sup>36</sup> No significant difference between FIRB and AIRB banks is observed for the sovereign and bank asset classes.

<sup>36</sup> See subsequent section on EAD (section 5.2).

Comparison of FIRB and AIRB – average Risk Weights

Table 8

	Mean	Median	Minimum	25th Percentile	75th Percentile	Maximum	No. of Banks
<b>AIRB</b>							
All	31.4	32.7	9.2	26.1	42.7	77.2	67
Corporate	44.8	48.9	24.3	41.4	58.0	108.9	61
Sovereign	3.1	4.1	0.2	1.8	7.6	46.3	44
Bank	18.0	17.2	4.5	13.2	24.9	49.0	49
<b>FIRB</b>							
All	32.6	32.6	2.2	21.8	39.8	78.5	35
Corporate	55.7	57.1	5.3	49.8	64.8	93.3	30
Sovereign	2.2	4.2	0.0	2.9	8.3	21.6	22
Bank	16.4	17.9	1.4	14.2	22.5	39.3	28

### *Treatment of defaulted exposures*

Another possible practice-based driver of RWA variation is the different rules across jurisdictions for calculating RWAs for defaulted exposures. Most jurisdictions follow the Basel text<sup>37</sup>, but a small number have adopted alternative approaches, such as effectively risk weighting defaulted exposures at 100%. Even among jurisdictions that follow the Basel text, there can be significant variability in risk weights for defaulted exposures since there are varying practices in estimating best estimate of expected loss (BEEL). The importance of defaulted exposures in explaining overall RWA variation depends on both the variation in risk weights for defaulted exposures and the proportion of exposures in default (driven by banks' actual defaults and write-off policies).

The Committee finds that risk weights for defaulted exposures vary considerably across banks for all asset classes (Table 9). All of the variation in risk weights for defaulted exposures can be attributed to AIRB and retail IRB banks as banks using the FIRB approach for wholesale exposures do not have to calculate RWAs for defaulted exposures.<sup>38</sup>

<sup>37</sup> RWAs for defaulted exposures are the larger of zero and the product of EAD and the difference between the bank's estimate of downturn LGD and its best estimate of expected loss (BEEL), multiplied by a factor of 12.5. BEEL can differ from the downturn LGD estimate in that it reflects current economic circumstances.

<sup>38</sup> Instead, the capital charge for such FIRB exposures is captured solely through EL for FIRB banks.

Defaulted exposures – Risk Weights, share of exposures and RWA

Table 9

Asset Class	Risk Weight (%)			Share of Exposures (%)			Share of RWA (%)		
	Mean	25th	75th	Mean	25th	75th	Mean	25th	75th
Corporate	39	21	139	3.4	1.2	5.9	2.8	1.2	6.2
Retail	57	11	106	2.8	0.8	3.4	5.8	0.7	8.2
Bank	27	0.0	102	0.4	0.0	0.5	0.6	0.0	0.7
Sovereign	19	0.0	63	0.3	0.0	0.1	1.9	0.0	1.2
Overall	55	20	110	1.9	0.9	2.9	3.2	1.3	5.8

### *Treatment of securitisation exposures*

The treatment of securitisation exposures is another possible practice-based driver of RWA differences. Basel 2.5 introduced new risk weights and deduction requirements for certain securitisation exposures. Under Basel III, some securitisation exposures which were subject to deduction, or could be treated through either deduction or risk weighting at the discretion of the bank, must now be risk weighted at 1,250%. As different jurisdictions are at varying stages of implementing Basel 2.5 and Basel III, the differential treatment of securitisation exposures can give rise to RWA variations. The differential treatment of securitisation exposures as a driver of RWA variation should, however, become less of an issue over time as more jurisdictions transition to Basel III.

### 3.2.6 Materiality of IRB parameters

The Committee performed multivariate regression analysis of panel data extracted from the CMG dataset from December 2008 to December 2011 to assess the relative importance of EAD-weighted IRB risk parameters as sources of RWA variations.<sup>39</sup>

The analysis suggests that PDs<sup>40</sup> are a key source of RWA variations – notably for the corporate asset class, but also for the retail, sovereign and bank asset classes. LGDs seem to be very significant in explaining RWA differences for retail exposures as a group<sup>41</sup> and significant for the bank asset class, and have some impact on the corporate and sovereign asset classes.<sup>42</sup> Maturity does not appear to be an important source of RWA variations (Table 10). The results are broadly consistent with the variability in PD and LGD estimates across different asset classes (Annex 3, Tables 2 to 5).

<sup>39</sup> While the approach contains model limitations, it could be useful in helping identify relevant IRB parameters for further study under the bottom-up benchmarking exercise and thematic reviews of practice-based drivers.

<sup>40</sup> All IRB parameters (PD, LGD, Maturity) were EAD-weighted.

<sup>41</sup> That is, residential mortgages, revolving credits and other retail exposures in aggregate.

<sup>42</sup> In contrast, the analysis in section 4.2.4 suggests that LGD may be a more significant source of RWA variation, at least for the corporate and sovereign asset classes. To some extent, the difference in results may reflect differences in obligor coverage. The bottom-up analysis in section 4.2.4 covers a relatively narrow range of high-quality obligors; the likely narrower range of PD estimates for these obligors leaves less scope for in-sample PD variation than in the top-down analysis, which covers the entire corporate and sovereign asset classes with a likely wider range of PD values.

Relative significance of IRB parameters in explaining RWA variations Table 10

	PD	LGD	Maturity
Corporate	***	*	–
Retail	**	***	n/a
Sovereign	**	*	–
Bank	**	**	*

\*\*\*Very significant.

\*\*Significant.

\*Some impact.

– No observed impact.

## 4. Portfolio benchmarking analysis

In addition to the top-down analysis described in the previous section, the Committee conducted a hypothetical portfolio exercise (HPE) among 32 major international banks to explicitly analyse practice-based differences of RWAs through consideration of specific, commonly held obligors and exposures. As discussed above, the top-down analysis suggests that much of the RWA variation (up to three quarters) appears to be identifiably related to risk; the bottom-up analysis of the HPE therefore focuses on part of the remaining RWA variation.

### 4.1 Structure of the bottom-up portfolio benchmarking exercise

The HPE focused on types of wholesale credit (sovereign, financial, and large-corporate borrowers) that are generally regarded as “low-default.” A list of borrowers was provided to all participating banks, with the banks requested to provide PD estimates for each borrower and, if they use the AIRB approach, downturn LGD estimates for the exposure. The exercise was “hypothetical” in the sense that the nominal exposure amount was not specified, and in most cases the exposure type was specified as senior unsecured, regardless of the actual exposure type a bank might normally have. However, participating banks were instructed to provide risk parameters only if they actually had exposure to that specific obligor, either on- or off-balance-sheet, which helped ensure that the responses reliably reflect estimates the participants actually use to calculate RWAs.

All banks identified as global systemically important banks (G-SIBs) were considered for participation; adjustments were made to that list when the wholesale credit business of a G-SIB was not sufficiently international in scope or was of minor importance compared with other lines of business, or where the addition of other banks would add valuable depth to the analysis. Ultimately, 32 banking organisations from 13 jurisdictions participated; 17 were European, seven were from North America, and eight were from Asia and Australia.

The list of borrowers and exposures – the composition of the hypothetical portfolio – was constructed with a view to achieving a high degree of overlap among participating banks.<sup>43</sup> The final sovereign sub-portfolio consisted of 46 of the largest sovereign debt issuers. An initial list of financial institutions was drawn from the list of G-SIB candidates, and supplemented with additional suggestions from national supervisors; the final sub-portfolio comprised 77 banks.

A set of large corporate obligors was drawn initially from DealScan, a database that provides information on debtors and their creditors in the syndicated loan market.<sup>44</sup> Participating banks were asked to provide data for any of these syndicated loans to which they actually had exposure. In addition, participants were asked to provide the PD and downturn LGD estimates assigned to any of the corporates for which they had any type of credit exposure (not just a syndicated loan), assuming the exposure to the obligor reflected a senior unsecured position. This latter group is referred to as the “Corporate-Hypothetical” sub-portfolio, while the list of actual syndicated credits (for each bank, a subset of the longer “hypothetical” list) is referred to as the “Corporate-Actual” sub-portfolio. The final corporate-hypothetical portfolio contained 1,287 unique names. A little more than half of those had an active rating from either Standard & Poor’s, Moody’s or Fitch as of October 2012; of the rated obligors,

<sup>43</sup> A desire for broad coverage was balanced against a desire to minimise reporting burden in order to ensure good participation by banks.

<sup>44</sup> Corporates from the DealScan database were included if they were recorded as having exposure to at least four of the banks participating in the HPE.

two thirds were investment grade, and one third below investment grade.<sup>45</sup> Table 11 characterises the responses from the 32 participating banks; this shows the number of PD responses provided by each bank. The numbers for LGD responses are similar. Observations were excluded from analysis if any bank rated the obligor as being in default.

Number of observations (for PDs)				Table 11
	Sovereign	Bank	Corporate Hypothetical	Corporate Actual
<b>Asia and Australia</b>				
1	31	70	216	142
2	13	67	443	288
3	3	26	140	79
4	0	52	17	0
5	13	61	90	61
6	21	71	413	261
7	11	31	83	85
8	3	42	346	14
<b>Europe</b>				
1	0	5	134	67
2	23	35	413	355
3	25	75	284	152
4	35	62	179	117
5	15	58	51	33
6	10	47	149	122
7	41	76	305	54
8	26	67	400	196
9	12	63	103	72
10	5	20	66	45
11	26	76	360	66
12	18	70	436	311
13	9	64	234	124
14	42	59	240	156
15	38	63	371	179
16	43	76	491	364
17	11	45	28	2
<b>North America</b>				
1	43	75	727	433

<sup>45</sup> The largest concentration of the rated names (45%) was in the “BBB” rating grade. Slightly less than half of the corporate obligors were from North America, while Europe and Asia (together with other emerging markets) each accounted for about one quarter.

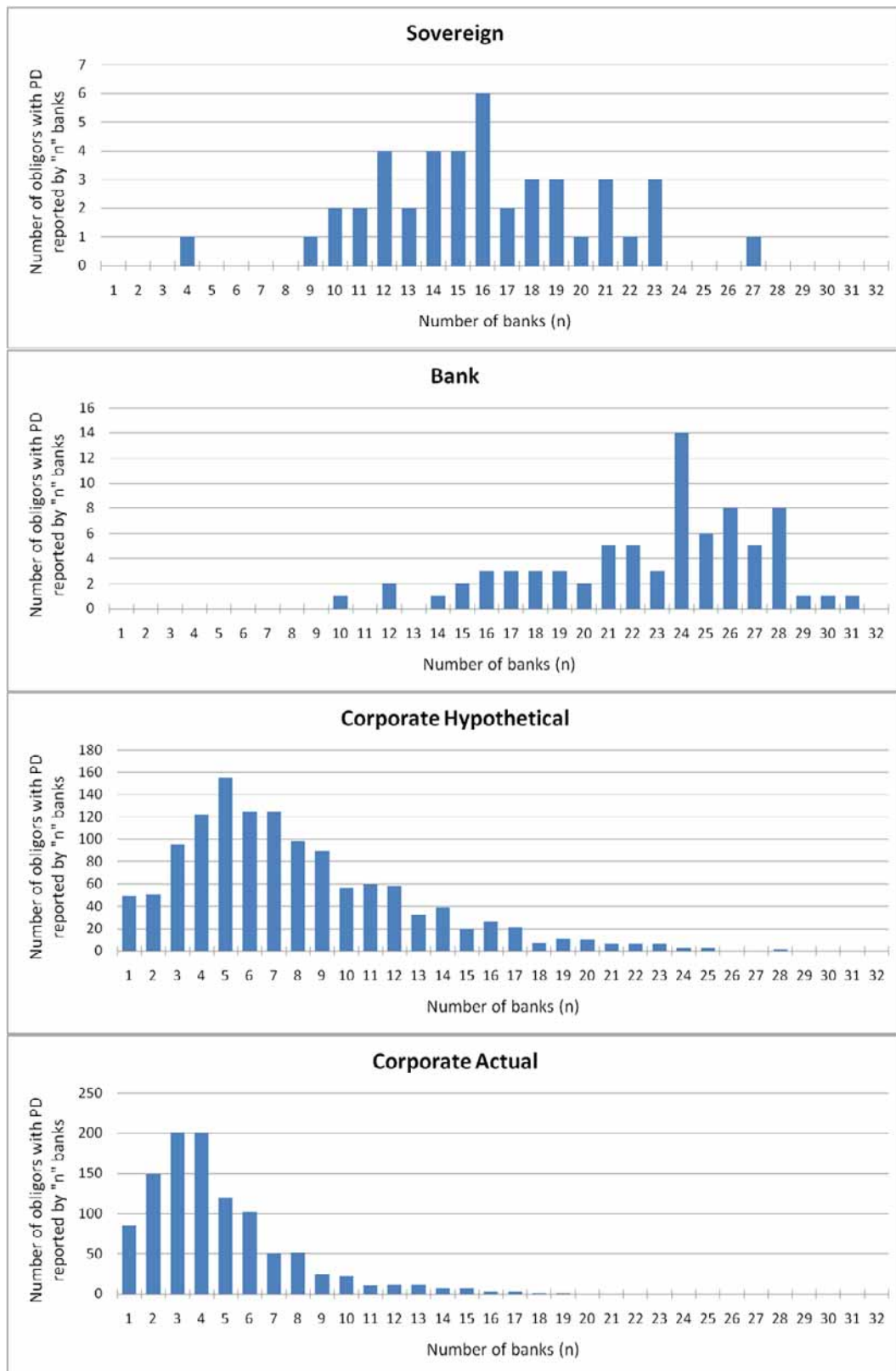
2	16	25	131	96
3	11	65	132	76
4	29	54	556	481
5	30	67	595	368
6	1	52	437	241
7	7	35	90	76
<b>Totals</b>	611	1,754	8,660	5,116

Number of obligors for which PD was reported; figures include only obligors for which the participating bank reported a non-zero exposure amount. Each row represents one bank.

The overlap in the hypothetical portfolio generally was very good for the sovereign and bank asset classes, and, as expected, a little less so for the corporate asset class. Chart 8 shows the number of obligors rated by various numbers of HPE participants, for each asset class. Thus, for example, there were six sovereign obligors for whom PD estimates were provided by 16 participating banks, one sovereign obligor covered by only four banks, and one covered by 27 of the participants. Most of the sovereign and bank counterparties were rated by more than half of the HPE participants. For corporates, there were a few hundred counterparties that were covered by only five or fewer of the participating banks; however, for more than a third of the corporate names, PDs were assigned by 10 or more participating banks, creating a substantial foundation for analysis. This is a fairly high degree of overlap for this asset class, judging from the experience of prior bottom-up portfolio exercises.<sup>46</sup>

<sup>46</sup> The HPE analysis generally excludes PD or LGD observations for which the reporting bank did not have an actual exposure. (The objective is to focus on exposures for which the IRB framework most clearly applies and for which banks are likely to exercise greater diligence in deriving IRB parameter estimates.) Also, much of the analysis is limited to exposures for which at least four banks provided estimates, since the purpose of the HPE was to consider overlapping exposures with coverage that would allow meaningful cross-bank comparisons. Finally, observations rated as defaulted by at least one participating bank (a total of three sovereign obligors and 16 corporate obligors) were omitted from the analysis.

Chart 8: Distribution of HPE obligor coverage



Bar height indicates the number of obligors within the HPE portfolio for which PD estimates were received from various numbers of participating banks shown on the horizontal axis.



The results of the HPE are most directly representative of the specific sample portfolio used in the exercise. One measure of the degree to which the results are representative more generally is the share of each bank's portfolio that is encompassed by the exposures covered in the HPE (Table 12). The HPE covers more than 40% of sovereign EAD on average. Coverage for bank exposures was more limited, at around 30%, and for corporates more limited still, at a little less than 10% of that asset class on average. Table 12 also indicates that the percentages of RWA covered are somewhat less than the corresponding shares of EAD, a difference that may reflect the necessary reliance of the HPE on larger and better-known obligors in order to achieve overlap across institutions.

Percentage of EAD and RWA covered by HPE at participating banks				Table 12
	Mean	Median	25% percentile	75% percentile
<b>EAD</b>				
Sovereign	44.2	41.0	14.4	68.2
Bank	31.8	27.9	17.3	43.7
Corporate	9.6	8.1	5.2	10.6
<b>RWA</b>				
Sovereign	30.5	25.9	8.8	47.2
Bank	24.9	23.3	13.0	32.1
Corporate	8.5	6.8	4.5	10.6

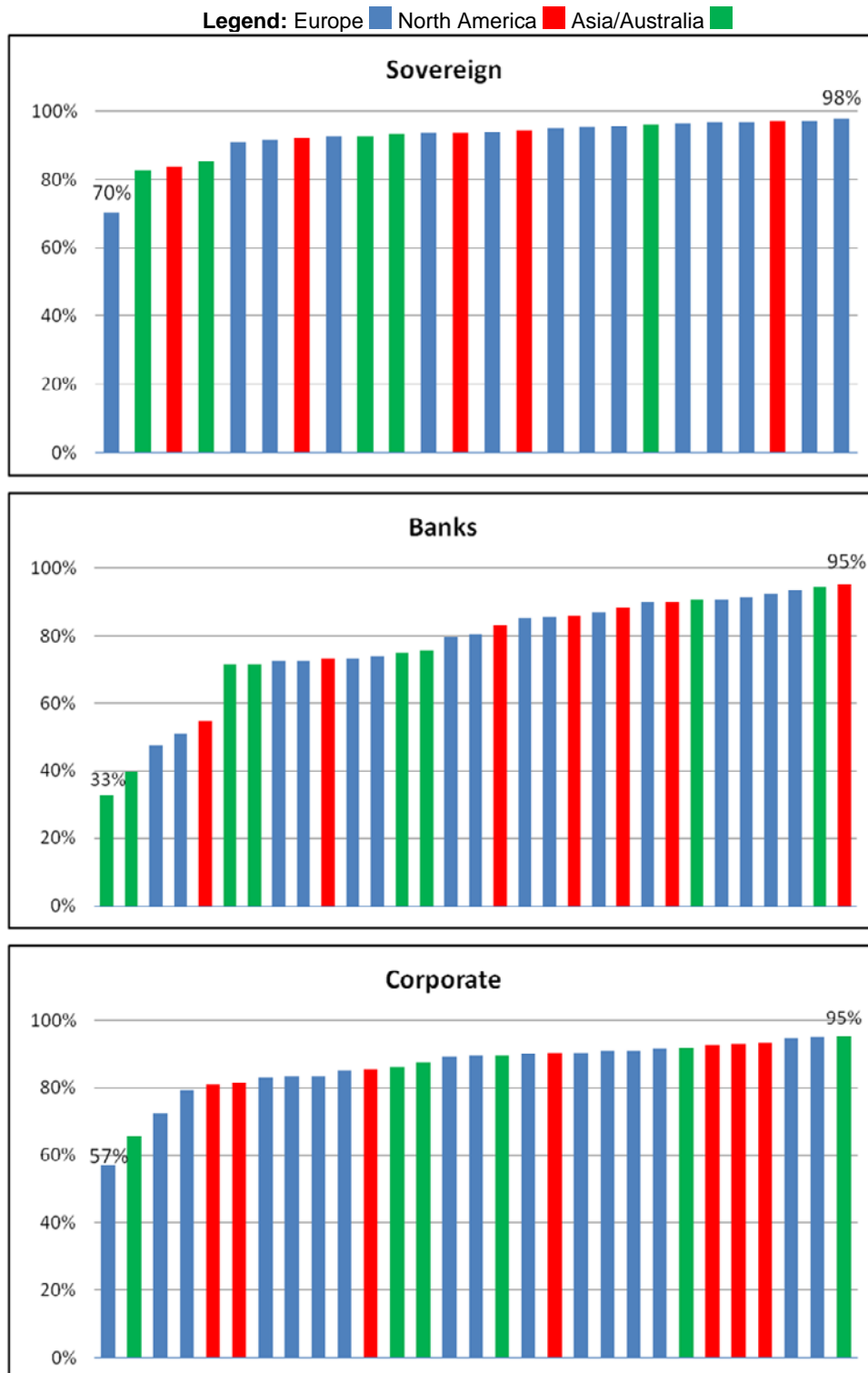
## 4.2 Findings

### 4.2.1 PD and LGD

There is considerable agreement across banks with regard to the relative default risk of obligors in the HPE; that is, when considering two different obligors, banks generally agree on which one should be rated the riskier. This is evident from generally high rank correlations in the PD estimates assigned by the banks as illustrated by the bank-by-bank rank correlations in Chart 9, particularly for sovereign exposures.<sup>47</sup> Rank correlations for risk weights are also high. Despite the generally high rank correlations with the benchmarks, a few banks appear as outliers with notably lower rank correlations.

<sup>47</sup> To compute these rank correlations, a given borrower is ranked by the PD assigned by the bank, and then again by the median PD assigned to the borrower by all banks within the HPE; the rank correlation is the coefficient of correlation between these two rankings. The calculation included only borrowers for which PD estimates were provided by at least four banks.

Chart 9: PD correlation



Rank correlation between PD estimates provided by each bank and benchmark PD (cross-bank median PD for each obligor); each bar represents one bank. Banks with fewer than 10 observations in a portfolio are omitted from the corresponding graph.

However, the levels of PD estimates differ across banks; thus, while rank ordering may be very similar, the calibration of absolute risk is less so. Master scales provided by banks display considerable variation in the PD estimates associated with the lower-quality, or higher-risk, rating grades, but with no

particular regional pattern. Results do appear to reveal a degree of “home bias” by region, in that some banks tend to assign lower PD values to borrowers within their own region.

LGD estimates show relatively little variation across exposures for many of the banks, which perhaps is not surprising since much of the HPE is based on hypothetical low-default senior unsecured exposures. However, the levels of LGD estimates assigned to common exposures differ across participating banks. In Chart 10, each vertical line represents one obligor in the HPE; the central dot represents the mean, the thick segment represents the inter-quartile range (the middle 50% of observations), and the thin “whisker” line represents the entire interval between the minimum and the maximum value of the parameter.

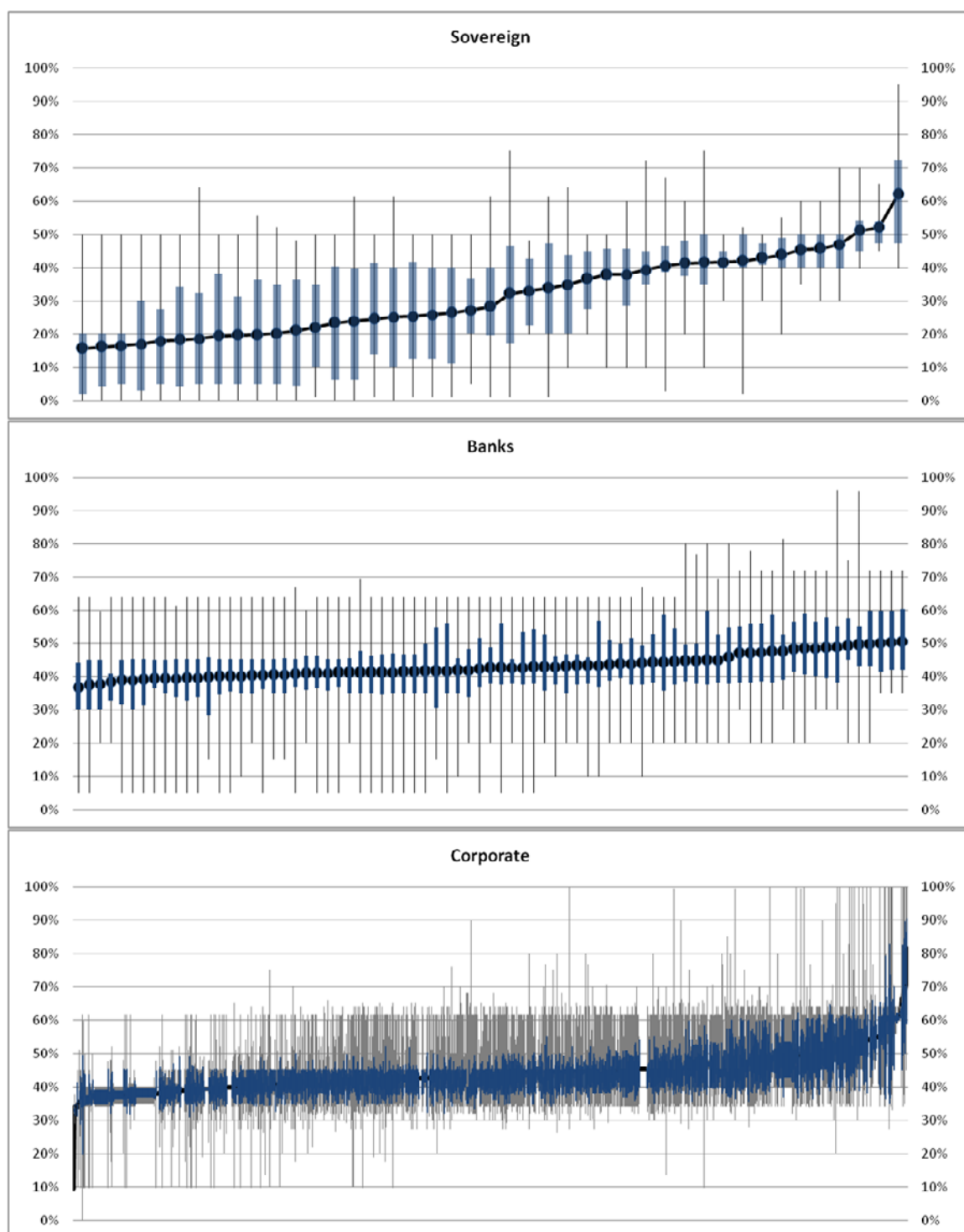
A notable feature of the LGD data is that many banks assign only a few distinct values of LGD across the portfolio. This is visible in Chart 10, from the horizontal alignment of the high and low LGD estimates for many of the obligors, which is caused by one or more of the banks assigning a relatively high (or low) LGD to all borrowers in a particular asset class. Indeed, many banks apply what could be described as a “modified FIRB approach”, assigning a fixed LGD value to most of the portfolio, with the fixed values possibly being quite different from bank to bank.

The height of the vertical lines in Chart 10 indicates substantial variation across banks in the levels of LGD for most obligors. Variation is especially evident in the sovereign and bank portfolios:

- For many of the sovereign obligors, the inter-quartile range of banks’ LGD estimates spans 25 to 35 percentage points, which would have a direct and very substantial impact on variation in RWA and minimum capital required for those obligors.
- For the bank portfolio the inter-quartile range is considerably narrower than for sovereigns, although the full range of the data (the length of the “whisker”) is at least as broad.
- LGDs for the corporate obligors lie in a somewhat narrower range.

These results indicate that differences in LGD may be a significant source of variation in RWAs across banks.

Chart 10: LGD distribution for each hypothetical exposure



Each vertical line represents one exposure from the HPE for that asset class. The central dotted line indicates the average LGD, the thicker bar covers the estimates of LGD from the middle 50% of the banks (the inter-quartile range), and the lighter "whisker" line indicates the range from the minimum (lowest LGD assigned by any bank) to the maximum. Corporate obligors displayed only if 10 or more observations were available.

#### 4.2.2 Risk Weights and capital ratios

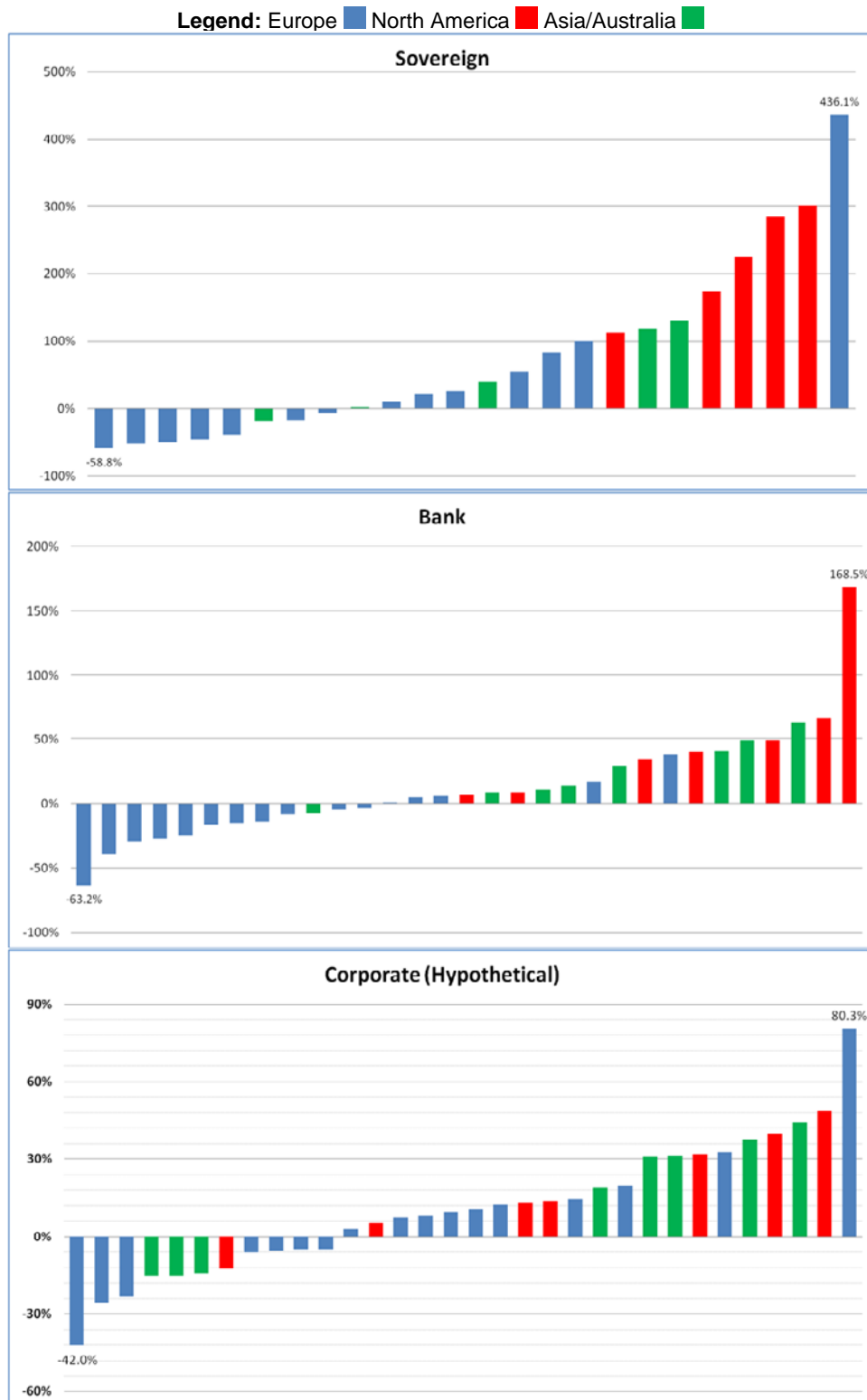
Differences in the PDs and LGDs assigned to borrowers and exposures cause risk weights to vary across banks. For each obligor rated by a bank, the risk weight assigned by the bank (based on the reported PD and LGD) can be compared to a benchmark risk weight calculated as the median across all banks reporting PDs and LGDs for that particular obligor. Percentage deviations from the benchmark can then be computed across all the obligors in the HPE to which the bank has an actual (non-zero) exposure. The three panels in Chart 11 show the distribution of the mean percentage deviations for each bank in the HPE, for each asset class.<sup>48</sup>

Notable outliers are evident in each asset class, with the corporate asset class showing the tightest clustering of banks around a central tendency, and the sovereign asset class showing the greatest variation, although to some extent these differences reflect differences in the general level of PD estimates for the respective asset classes. A regional pattern that emerges is that North American banks (in red) generally have above-average risk weights. Banks from Asia/Australia (green) and Europe (in blue) do not show any strong pattern overall, as banks from those regions can be found at both ends of the scale, with some exception for Europe with regard to the bank asset class.

The application of estimates based on middle-market data to large investment grade borrowers covered by the HPE surfaced during on-site discussions at a number of the banks that appear as outliers. Another common theme was the limited amount of data available for LGD estimation at many banks for low-default portfolios. As a result, an apparent explanation of certain of the outliers was the adjustment of estimates (notably LGD) to compensate for the lack of reliable internal data for estimation, largely based on expert judgement. As these examples illustrate, there can be many explanations for differences in risk weightings across banks, and the fact that a bank is an outlier does not necessarily mean its estimates and risk weights are wrong. A thorough understanding of the differences would require detailed supervisory investigation of each case.

<sup>48</sup> Obligor was included in the analysis only if data were reported by at least four banks. Banks were included in the chart for a given asset class only if they reported data for at least 10 exposures in the HPE for that asset class; this led to the inclusion of 25 banks for the sovereign asset class, 31 banks for the bank asset class, and 32 for the corporate hypothetical.

Chart 11: Risk Weights based on reported PDs and LGDs



Mean percentage difference from cross-bank median risk weight as benchmark; each bar represents one bank, with regions indicated by colours.

The ultimate impact of observed differences in risk weights at the individual counterparty level depends on how a bank's actual exposure amounts are distributed across its counterparties. The percentage deviations used in the charts above in effect assume that exposures to all counterparties are equal; however, this uniform-EAD assumption would understate the impact for a bank whose exposures tend to be concentrated in counterparties for which the PD, the LGD, or both diverge more from the benchmark, or would overstate the impact in the opposite case. The HPE did not collect actual exposure amounts, so the ultimate impact cannot be computed directly from the data.<sup>49</sup>

The importance of the uniform-EAD assumption was assessed through simulation exercises that measured the impact of portfolio mix under various reasonable assumptions about portfolio composition. The simulations revealed that the relative positions of banks remained generally consistent – banks with relatively high risk weights based on uniform EADs also exhibited higher risk weights for the simulated portfolios based on other distributions of EAD, and similarly for banks with relatively low risk weights. However, differences in actual portfolio composition (as opposed to uniform EADs) can lead to material differences in the level of risk weights for individual banks, indicating a lack of precision in the current results that warrants some caution in their interpretation.

To put the risk weight variation in perspective, a two-step analysis illustrates the potential impact on capital ratios. In the first step, RWAs are adjusted for each bank to approximate the RWAs if the bank were to apply the benchmark risk weights (ie the median risk weights across all banks in the sample) rather than its own risk weights. Assuming that the risk weight deviations observed in the HPE are broadly representative for the associated asset class (sovereign, bank, or corporate) for each participating bank<sup>50</sup>, the mean deviation from the benchmark can be used to approximate what each bank's RWA for a given asset class would be if the benchmark risk weights were used.<sup>51</sup> Applying this adjustment to the sovereign, bank and corporate asset classes<sup>52</sup> using the relative RWA contributions for the three wholesale asset classes from the CMG data for each bank in the sample generates an adjusted RWA figure. If a bank uses PD and LGD estimates that generate lower risk weights on average, the adjustment to the benchmarks would result in higher RWA (and hence lower capital ratios), with the opposite applying to a bank that has higher risk weights on average. All other components of RWA (other than sovereign, bank, and corporate credit) are assumed to be unchanged.

In the second step, each bank is assumed to currently report capital equal to 10% of RWAs. Holding the absolute amount of capital constant at this level for each bank, the adjusted RWA figure from the first step is applied, and the capital ratio for each bank is recalculated.<sup>53</sup> Chart 12 shows the results, displayed in terms of the percentage point difference from the assumed initial capital ratio of 10%.<sup>54</sup>

<sup>49</sup> Actual EAD amounts were not collected from banks as part of the HPE, due to concerns about data sensitivity.

<sup>50</sup> This is a potentially important assumption, since the obligors included in the HPE were selected to enhance the degree of overlap across banks, rather than to be representative of these portfolios.

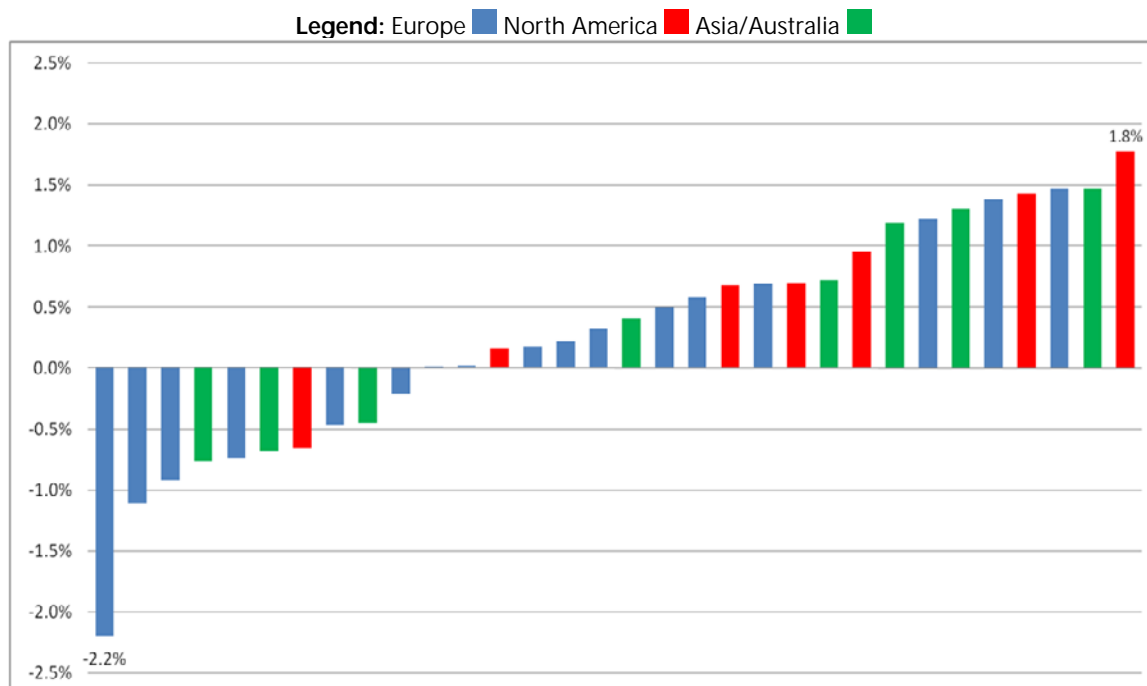
<sup>51</sup> Specifically, if the mean risk-weight deviation for an asset class from the HPE is D% and the RWA for that asset class is equal to A, then using the benchmark risk weights the RWA for that asset class would be  $A/(1+D\%)$ .

<sup>52</sup> These asset classes represent, on average, 42% of the EAD of banks participating in the HPE, based on CMG data.

<sup>53</sup> That is, the adjusted capital ratio is equal to 10% of actual RWAs divided by the adjusted RWA figure from the first step.

<sup>54</sup> The differences scale up or down directly with the assumed capital ratio; with a capital ratio of 15% (instead of the assumed 10%), the impact would be 1.5 times greater, ie 3.3 percentage points for the bank on the far left and 2.3 percentage points for the bank on the far right.

Chart 12: Illustrative impact on capital ratios



Change from 10% capital ratio if risk weights from bottom-up benchmarking are adjusted to the median. Each bar represents one bank. The chart assumes that variations observed at each bank for the hypothetical portfolios are representative for the entire sovereign, bank, and corporate portfolios of the bank and are adjusted accordingly, but makes no other adjustment to RWA or capital. The chart uses mean risk weight deviations for each bank, and non-zero exposures only.

At one extreme (at the far left of Chart 12), one bank would report a capital ratio 2.2 percentage points lower than the 10% benchmark if its risk weights were adjusted to reflect the cross-bank benchmark risk estimates; this bank assigns PD and LGD estimates that tend to result in risk weights below those of other banks and would therefore see its capital ratio decrease if it used industry median credit risk parameters. At the other extreme (far right of the chart), one bank would report a capital ratio 1.8 percentage points higher, because applying the benchmark risk weights would reduce its RWA. These are the extremes at either end of the distribution; 22 of the 32 banks lie within 1 percentage point of the 10% benchmark used in the chart, and only two of the banks show a capital ratio reduction exceeding 1 percentage point.<sup>55</sup>

The differences in capital ratios scale up or down directly with the benchmark capital ratio used, assumed to be 10% for the chart. Thus, an equivalent statement of the conclusion is that if the variation in risk weights observed for the HPE exposures is representative of the sovereign, bank, and corporate portfolios at these banks more generally, such variation could cause capital ratios for otherwise identical banks to differ by up to 22% from a given initial capital ratio. On average for the 32 banks, the deviation (either positive or negative) is 8%.

<sup>55</sup> Separate analysis suggests that a bank with a portfolio-wide PD deviation of half a rating grade and LGD deviation of 4 percentage points would exhibit a capital ratio deviation approximately 0.6 percentage points above or below a given benchmark capital ratio. About half of the banks differ from the benchmark by less than 0.6 percentage points.

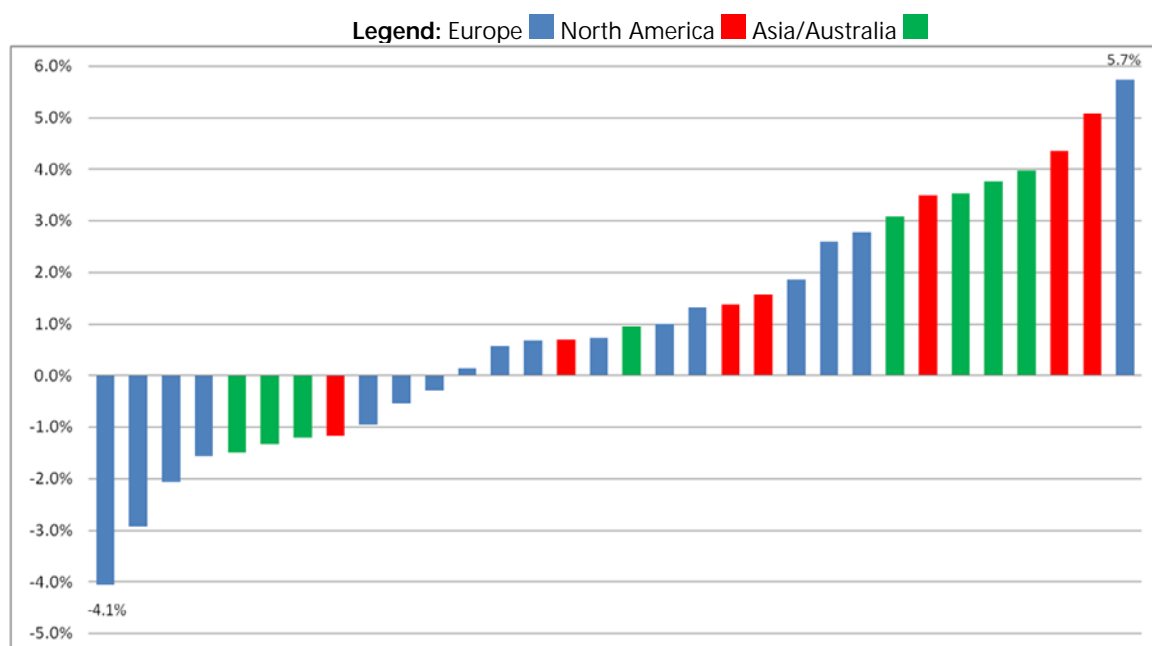


The analysis in Chart 12 assumes that the extent to which a bank's risk weights deviate from the cross-bank median benchmark as observed in the HPE for the sovereign, bank and corporate portfolios applies only to those portfolios, but not to other parts of the banking book; thus, the implicit assumption is that each bank looks "average" with regard to other credit types (such as retail credit) and other risk types. On average, sovereign, bank, and corporate portfolios account for approximately 40% of total credit RWAs for the HPE banks.

An alternative approach to assessing the impact of those deviations is to assume that the average risk weight deviation for all other parts of the banking book (such as retail credit) at each participating HPE bank matches the weighted average deviation for the wholesale exposures covered in the HPE; in effect, the bank is assumed to deviate from the mean in other credit types in a way that corresponds to its observed treatment of the three wholesale asset types. In that case, the potential impact on capital ratios is substantially larger (Chart 13). In general terms, the impact from Chart 12 is scaled upward for Chart 13 by the ratio of total credit risk RWAs to the combined RWAs of sovereign, bank, and corporate credit. However, there are important reasons why this result should be viewed with caution:

- the rank-ordering of banks is not the same for the three HPE portfolios assessed; this suggests that a simple "scaling up" approach may not appropriately capture differences in rank ordering across other, more diverse, portfolio types.
- other credit risk categories may have more extensive data histories, which may allow for more accurate quantitative calibration, and less need for adjustments based on expert judgement.

Chart 13: Illustrative impact on capital ratios if deviations apply to entire Banking Book



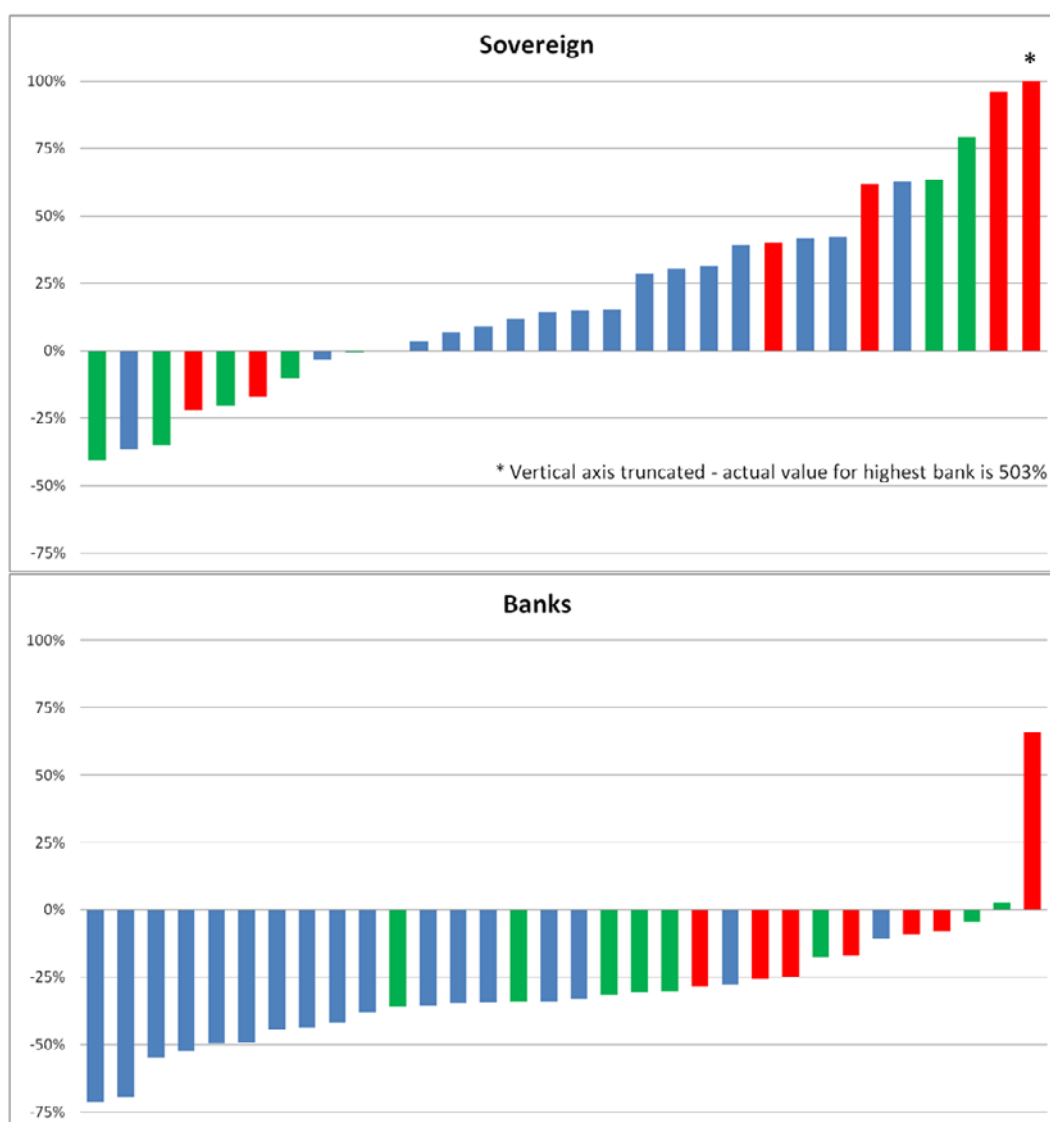
Change from 10% capital ratio if risk weights from bottom-up benchmarking are adjusted to the median and applied to the entire banking book. The chart uses mean risk weight deviations for each bank, and non-zero exposures only.

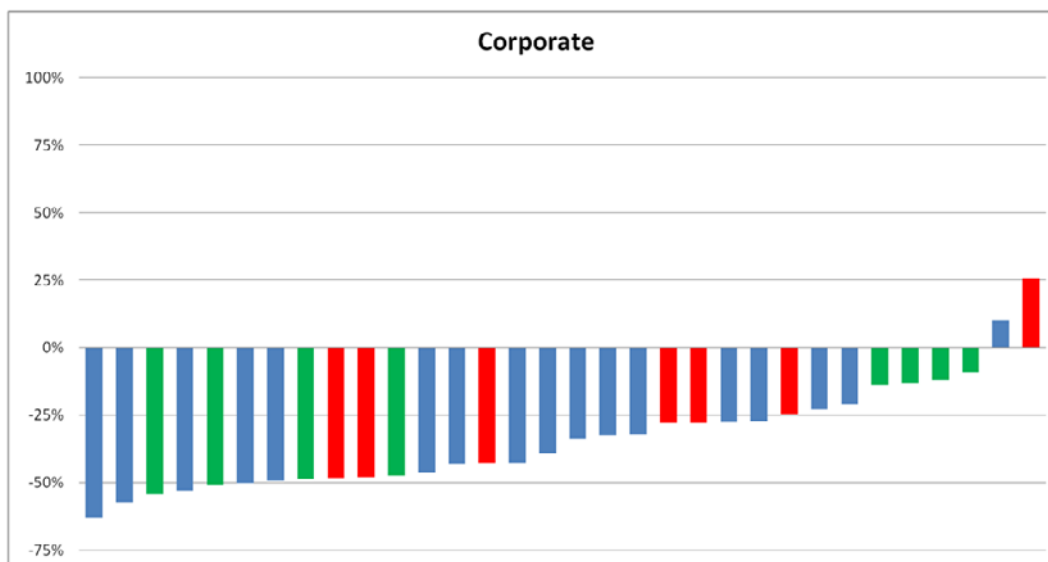
To provide a more realistic measure of the full impact on banks' capital ratios, an HPE analysis would be needed that covers the entire banking book, linked to similar exercises for market risk and operational risk. The Committee plans to extend the HPE analysis accordingly in future work with a view to providing a more complete assessment.

### 4.2.3 IRB vs Standardised Approach Risk Weights

RWAs under IRB using the PD and LGD estimates from the HPE tend to be lower than would be obtained under the standardised approach, although this is not the case for all banks (Chart 14). The relationship varies across banks and by asset class; while IRB risk weights are generally lower than standardised risk weights for bank and corporate exposures (on average for all but two of the participating banks), IRB risk weights are higher than standardised risk weights for sovereign exposures on average, with 20 of the participating banks showing higher IRB sovereign risk weights than the standardised risk weights on average. While the focus of the study is on variation in RWAs, future analysis could incorporate additional assessment of the level of RWAs as well.

Chart 14: Difference between IRB and Standardised Risk Weights





Differences reported as percentage of the Standardised risk weight. Positive values indicate that average IRB risk weights based on bank-reported PD and LGD exceed Standardised risk weights for the same exposures; negative values indicate that IRB risk weights are lower than Standardised risk weights.

#### 4.2.4 Relative impact of PD and LGD

The relative impact of PD and LGD can be assessed by fixing one parameter at the benchmark for every exposure in the HPE data while allowing the other to vary as observed, and measuring the impact on risk weight variation. The results of this type of analysis are presented in Table 13.

The first row in the table shows the results of calculating for each bank the median risk weight differential (the median of the percentage differences from the cross-bank medians as benchmarks for each exposure) and then computing the standard deviation across the banks participating in the HPE. The second row shows the effect of eliminating variation due to differences among banks with regard to PD, by setting the PD for each exposure equal to the cross-bank benchmark (the median for that exposure); the variation is then due solely to differences with regard to LGD. The standard deviation of risk weight differentials is reduced by 15 to 30% for the bank and corporate asset classes, and by almost 50% for sovereign.

The final row in the table shows the effect of eliminating disagreement with regard to LGD by setting LGD for each exposure in the HPE to be equal to its cross-bank median for every bank, while using the actual, observed PD for each exposure at each bank to recalculate the risk weights; the table displays the resulting standard deviations. The reductions in variation as measured by the standard deviation are larger than was the case for PD for every asset class, with reductions ranging from 70% for the sovereign asset class to 45% for bank and 30-35% for corporate.

Relative impact of PD and LGD variation				Table 13
	Sovereign	Bank	Corporate (H)	Corporate (A)
With actual observed PD, LGD	1.10	0.43	0.22	0.23
Remove variation in PD	0.57	0.31	0.16	0.20
Remove variation in LGD	0.31	0.24	0.14	0.16

Standard deviations of risk weights computed across banks participating in the HPE (based on within-bank median deviations of risk weights from the cross-bank median as benchmark). For sovereign, for example, the standard deviation of the median relative deviation is 110%.

## 5. Range of practices

In addition to the top-down and bottom-up analysis, the Committee used surveys of the range of practice to investigate actual, specific practices in particular areas.<sup>56</sup> The Committee has catalogued, mostly based on supervisory experiences, known areas in which industry or supervisory practices differ, and conducted more in-depth reviews using survey-based information on three initial areas: estimation of EAD, estimation of long-run default probabilities, and calculation of maturity for wholesale credit exposures.

### 5.1 Identification of areas of potential differences in practice

By reviewing potential practice-based drivers of RWA differences based on existing supervisory knowledge and judgement, the Committee identified the following six broad categories of drivers to be the most significant. These categories identify areas where policy changes could be considered to reduce the range of variation.

#### 5.1.1 Credit Risk approach (Standardised/FIRB/AIRB)

In many jurisdictions, the IRB approaches are rolled out over time, with a portfolio-by-portfolio migration from the Standardised approach to the IRB approaches. This leads to variation across banks and over time in the percentage of the portfolio treated under the different approaches (Standardised, FIRB and AIRB). The potential impact may be magnified if the roll-out period is lengthy, or when permanent exemptions from IRB are provided for certain asset classes, such as sovereign exposures. Also, some jurisdictions require AIRB treatment for all material portfolios, with no phasing of roll-out; RWAs for banks in such jurisdictions are likely to differ from those in jurisdictions that permit temporary or permanent partial use (see earlier discussion of Chart 4).

Some variations stem from differences between the approaches. For example, internal estimates of EAD and LGD under AIRB may be quite different from those specified under FIRB, with an impact on RWA of potentially high magnitude. As another example, a significant impact may also arise from the application of a zero CCF for uncommitted and unconditionally cancellable lines of credit under Standardised and FIRB approaches, whereas these lines can receive a positive CCF under AIRB.

#### 5.1.2 Definition of default

The regulatory framework incorporates discretionary elements into the definition of default for some asset classes. Differences in the definition of default affect all estimated risk parameters, with some potential offsetting effects between PD and LGD (which may in turn be limited by the application of LGD floors). For retail obligors and public sector entities, explicit discretion is granted for supervisors to choose to extend the past due period in the default definition from 90 up to 180 days, and about half of the jurisdictions exercise discretion in this regard. The impact on resulting RWA is regarded as potentially significant. Another significant difference is whether days past due is defined on a “time” basis, eg a borrower is in default when 90 days have passed since the borrower was up to date, or a “money” basis, when amounts overdue are equivalent to 90 days’ payments. There are also differences across jurisdictions and among banks in the application of the “unlikely to pay” element of the default

<sup>56</sup> In many cases, differences in practice are best explored through discussions among supervisors, or through surveys of financial institutions. Depending on the nature of the issues, on-site discussions with industry participants may also be one fruitful way to identify specific practices or policies and consider potential changes.

definition. Treatment of loan restructurings, re-ageing, and other elements related to default differ as well, with effects that individually may be moderate in magnitude but in combination could be more significant.

### 5.1.3 Margins of conservatism in risk parameter estimates

Banks frequently add (perhaps due to supervisory expectations or explicit requirements) a margin of conservatism to risk parameter estimates related to the likely range of estimation or other modelling errors – including deficiencies in data and model uncertainties – or to make estimates more forward looking. However, methodologies used for these adjustments – and the desired level of prudence – vary widely. Although conservative, this practice may create significant issues for validation and lead to variation in resulting RWAs of potentially significant magnitude.

### 5.1.4 Adjustments for cyclical effects

The impact of cycles on credit portfolios, risk models, and the data used for parameter estimation are all areas in which knowledge is limited and practices continue to evolve and to vary. Even banks that have devoted considerable thought and resources to this issue struggle to produce robust estimates of long-run PD. The result is variability in outcomes across banks for the same risk, and also variability over time as new methods and data are applied or corrections are made to existing methods. The magnitude of the impact on RWAs is likely to be high.

With regard to LGD, the requirement for incorporation of downturn effects is particularly challenging for consistency in RWAs. The definition of downturn is deliberately flexible in the Basel framework, and as a result the definitions of downturn used in practice by AIRB banks vary widely. Methods for incorporating downturn effects also vary widely. A general lack of relevant historical data makes the task of quantifying downturn effects even more difficult, especially in some emerging economies where it may be difficult to identify a relevant downturn period. The magnitude of the resulting impact on RWA can be high, given the proportional impact of LGD on RWAs and required capital. Many of the same points made regarding downturn effects and LGD also apply to EAD and the estimation of CCFs, although there is perhaps an even greater degree of uncertainty and fundamental differences regarding the impact of downturns on this parameter.

### 5.1.5 Risk parameters for low-default portfolios

A well-known quantification problem within IRB is the estimation of risk parameters (PD, LGD and EAD) for so-called “low-default” portfolios; the challenge is particularly acute for low-default wholesale portfolios with a small number of counterparties. The results can be significantly impacted by the choice of data sources and calibration techniques. In particular, large variability is sometimes observed in LGD estimates, with some very low estimates for highly rated sovereigns and banks. For EAD, lower CCFs than those applied under FIRB may be applied under AIRB, but with limited support from data. The resulting differences in risk quantification could have a high impact on resulting RWAs.

### 5.1.6 PD master scales

For many banks, the PDs assigned to obligor rating grades for wholesale exposures depend at least to some degree on the historical default rates for external agency rating grades that have been “mapped” to internal rating grades to create a so-called “master scale.” Not only do mapping practices differ, but there are observed differences in the historical default rates used for various external grades. These differences can lead to differences in PD assignment, even in cases where banks might agree about the rating grade associated with a given borrower.

## 5.2. Exposure at default (EAD)

Estimation of EAD may have a material impact on RWAs. The Committee conducted a survey to evaluate certain aspects of the range of practices in EAD estimation.

Because the survey was limited to committed revolving lending facilities in the corporate asset class, and only in the lenders' home jurisdictions, the results may not generalise to other types of credit exposures. However, analysis of the survey results generated a number of important observations related to practice-based variations in RWAs:

- The extent to which a bank differentiates EAD estimates across exposures in its own portfolio appears to be relatively limited. Factors such as covenant strength, maturity, utilisation and obligor risk rating were used to differentiate EAD estimates at only a handful of the banks, and their impact on estimates was relatively minor (although risk rating differences tended to have a somewhat more material effect).
- However, EAD estimates exhibit substantial variation across banks, even when certain notable outliers are excluded.
- Based on the EAD models provided by these AIRB banks, the average conversion factor applied to undrawn commitments is roughly 50%; this can be contrasted with the 75% CCF for such commitments under the FIRB approach.
- Many aspects of EAD estimation incorporate expert judgement, in part to account for deficiencies (or perceived deficiencies) in available data, which means the empirical basis for some estimates may be weak. While some of the variation across banks is due to such adjustments (eg for conservatism or for cyclical factors), survey results indicate that this is not likely to be a dominant driver of differences in EAD estimates across banks.
- The terms and structure of borrowers' obligations are often modified during the approach to default, but EAD estimation methods generally do not take these modifications into account in an effective way.

In addition, data challenges are notable, as estimates of EAD generally require data from actual defaults, and for some important portfolios (such as large corporate) default data are scarce; in many cases, banks use default data from one portfolio (such as SME) to develop estimates that are then applied to another type of credit (such as large corporate) where the estimates may not in fact be appropriate.<sup>57</sup>

## 5.3 Probability of default (PD)

PD estimation was identified as another source of potentially important risk weight variation across most of the major credit risk categories (or portfolios). Responses to a survey conducted by the Committee indicated that a majority of the participating jurisdictions have set long-run PD requirements that either diverge from or provide more detailed guidance than the Basel framework, in areas such as minimum data requirements and margins of conservatism. Further in-depth analysis of these local differences in

<sup>57</sup> The survey also revealed potential issues related to common EAD methods. For example, most banks have adopted one particular approach to EAD that involves estimating draws as a percentage of remaining undrawn credit lines; aspects of this approach – most notably, its instability when the remaining undrawn amount is small – appear to make it inferior (at least without modification) to other approaches that are available and are no more complex.

requirements related to long-run PD estimation would be needed to assess their contribution to RWA variation, if any.

Examples of material differences in practices included:

- *Definitions of a full economic cycle.* While most portfolios (three-quarters) used a definition that took into account a period with higher than average default rates, only 29% of the portfolios used this definition exclusively, with the others using that definition in tandem with other considerations, such as comparison with industry experience and official definitions of recessions. Close to a quarter of the portfolios used a definition of an economic cycle other than the options offered in the survey.
- *Length of the data series used for PD estimation.* While almost all the portfolios used more than five years of internal data for PD estimation, only a quarter of the portfolios used more than 10 years of internal data.
- *Strategies to address internal data limitations.* Some banks supplement internal data with external data while others adjust their PD estimates or hold additional capital as a buffer. There is greater use of external data for the corporate than for the residential mortgage portfolio, whereas adjustments to PD estimates are more common for the residential mortgage than for the corporate portfolio.
- *Adjustment of PD estimates.* More than half of the banks adjust raw PD estimates to reach final long-run PD estimates. Methods for doing so vary – some banks rely on internal default experience, while others refer to external default data and still others make judgemental adjustments. Reference to internal default data is more prevalent for the residential mortgage portfolio.
- *Combining data sources.* Approaches for combining data from various sources also differ. Some banks simply append one data source to another. Others adjust or weight the data to ensure comparability. Yet other banks do not combine data from different sources but use them for other purposes, eg defining a downturn period or extrapolating internal data.

Future analysis can potentially explore how these differences in practices affect banks' PD estimates and the relationship between PD estimates and observed default rates.

## 5.4 Maturity

Effective maturity (M) is computed from contract terms rather than estimated from data, and therefore is generally not subject to estimation errors, unlike other IRB parameters. As a result, differences in the maturity parameter across banks are likely to reflect pure differences in practice for similar exposures, which may be particularly amenable to convergence through additional guidance or clarification of rules.

The Committee drew on survey work conducted in 2010 related to the calculation of maturity for wholesale credit under the AIRB approach. Several variations in practices, primarily due to supervisory rather than bank choices, are evident from that survey work, including the following:

- Some jurisdictions calculate maturity based on the expiry date of a facility while others use the repayment date of a current drawing under the facility. While the facility expiry date and repayment date would be the same for non-revolving facilities, the repayment date can often be considerably earlier than the facility expiry date for revolving facilities, resulting in a lower value for the maturity input and therefore a lower RWA figure.
- Some jurisdictions that use the expiry date of a facility to calculate maturity nonetheless use the repayment date of a current drawing to calculate maturity for exposures that are exempted from the one-year maturity floor. This leads to inconsistent approaches between exposures above and below the floor.

- Where a borrower has the option to extend a facility, most jurisdictions would adjust the maturity input assuming extension takes place. There are, however, a number of jurisdictions that use the original expiry date of the facility to calculate maturity.<sup>58</sup>
- The scope of exemptions from the one-year maturity floor is uneven, as it is subject to national discretion – some jurisdictions would allow an exemption as long as there are no material relationship considerations that would put pressure on a bank to roll over a maturing transaction. Other jurisdictions do not allow such exemptions.

These and other areas related to maturity calculations may warrant future work to narrow the range of practice.

<sup>58</sup> In contrast, almost all jurisdictions do not take into account the potential for repayment or cancellation ahead of the contractual expiry date.



## 6. On-site discussions with banks

A series of direct discussions with 12 of the 32 banks from the hypothetical portfolio exercise (HPE) provided valuable additional insights into the issues identified through bottom-up analysis from the HPE, as well as through top-down analysis and surveys of the range of practice in specific areas. In some cases, on-site discussions identified problems with the data submitted for the HPE, leading to revisions to the data and to the analysis based on those data. The 12 banks represented nine jurisdictions and reflected a wide range of results above and below the HPE benchmark results.

The discussions confirmed that data and modelling choices are important drivers of RWA differences between the banks. Discussions with banks highlighted significant differences in the granularity of master rating scales and rating systems, as well as differences in the level of PDs assigned by different banks to internal rating grades that were mapped to identical external rating grades. There was wide variation in approaches to the modelling used to estimate LGDs and PDs. There was almost no commonality among the banks in the breadth and depth of reference data sets. Some of the underlying elements of estimation processes (such as the treatment of workout costs, discount rates and recovery timeframes) vary considerably across the set of banks visited.

Several themes emerged from the discussions. One was a general lack of data for the low default portfolios covered by the HPE. The quality of reference data used by banks for estimation also varied significantly. The lengths of time spanned by data sets were often short, and data were sometimes stale; for instance, two banks submitted HPE results based on reference data that did not cover the most recent global financial crisis. (In both cases, home supervisors had already directed the banks to redevelop the corresponding models.) For corporate exposures, many banks noted that their default data were weighted more heavily toward SME defaults than large corporate defaults. Some banks were able to segment the default data to distinguish between these different types of corporate credit, but others were not, and it appeared likely that this was a factor driving divergent estimates.

Judgement appeared to play a particularly important role for PD and LGD models in the sovereign portfolio, and to a lesser extent for models applied in the bank asset class. However, it was not the case that judgement-based models led to results that were either consistently more conservative or less conservative; rather, the introduction of judgement led to greater variation in both directions.

## Annex 1: List of existing studies

Alliance Bernstein. *Global Banking: What is behind the difference in RWA/asset ratios between US and European banks? Technical Report*, June 2011.

Arroyo, J.M., Colomer, I., García-Baena, R., and González-Mosquera, L.. "Comparing Risk-Weighted Assets: The Importance of Supervisory Processes". *Financial Stability Journal*, Banco de España, May 2012.

Australian Prudential Regulation Authority. *Assessing Differences in IRB Capital Requirements. Regulatory Report*, Australia, January 2012.

Banca di Italia. *Inside the labyrinth of RWAs: how not to get lost*, by Cannata F., Casellina S. and Guidi G.

Banco de España. *Internal Staff Analysis. Regulatory Report*, Spain.

Bank of China. *Supervisory Work Overview. Regulatory Report*, China, 2012.

Barclays Capital:

(1) *Bye Bye Basel? Making Basel more Relevant. Technical Report*, May 2012.

(2) *The Shrinking European bank sector – the RWA rumbles on. Technical Report*, May 2011.

(3) *Two hundred million Inputs. Can you trust risk weighting at European banks, Technical Report*, April 2011.

BNP Paribas:

(1) *Risk weights on the skinny side. Technical Report*, June 2011.

(2) *RWA to total assets: BNPP and JPM on par? Technical Report*, June 2011.

Bundesbank. *Internal Staff Analysis. Internal Working Paper*, Germany.

Bundesanstalt für Finanzdienstleistungsaufsicht. *Internal Staff Analysis. Internal Working Paper*, Germany.

Citigroup. *The Weighting Game – Basel Risk Weightings. Technical Report*, June 2011.

European Banking Authority. *Preliminary Analysis on RWAs. Regulatory Report*, 2012.

Federal Reserve Board of Governors. *Federal Reserve Wholesale Benchmarking Exercise. Regulatory Report*, BS&R Quantitative Risk Management & Wholesale Qualification Team, USA, January 2012.

Financial Services Authority. *Results of 2009 Hypothetical Portfolio Exercise for sovereigns, banks and large corporations. Regulatory Report*, UK, [www.fsa.gov.uk/pubs/international/sbc\\_hpe.pdf](http://www.fsa.gov.uk/pubs/international/sbc_hpe.pdf), March 2010.

Financial Supervisory Agency. *Internal Staff Analysis*, Japan.

International Monetary Fund (IMF):

(1) Das, S. and A.N.R. Sy, "How Risky Are Banks" Risk-Weighted Assets? Evidence from the Financial Crisis", WP 12/36, (2012).

(2) Le Leslé, V. and S. Avramova, "Revisiting Risk-Weighted Assets", WP 12/90, (2012).

National Supervisory Authorities. *Internal Staff Analysis. Regulatory Report*, France.

Ledo, M. "Towards more consistent, albeit diverse, risk-weighted assets across banks". *Estabilidad Financiera*, n. 21, Banco de España, 2011.

International Association of Credit Portfolio Managers and International Swaps and Derivatives Association (IACPM):

(1) *Economic and Regulatory Capital Benchmarking Studies. Technical Report*, 2010.

(2) *Economic and Regulatory Capital Benchmarking Studies. Technical Report*, 2006.

Monetary Authority of Singapore. *Capital and Credit Risk Analysis. Internal Staff Analysis. Regulatory Report*, Singapore, July 2011.

Mediobanca Securities. *Simulating the convergence of risk weighting. Technical Report*, February 2012.

Office of the Comptroller of the Currency. *Are Basel II Risk Weighted Assets Aligned with Risk? Preliminary Evidence from US Banks' Banking Book. Regulatory Report*, USA, March 2012.

Office of the Superintendent of Financial Institutions. *Internal Staff Analysis. Regulatory Report*, Canada, 2007.

## Annex 2: CMG data used for the analysis

The CMG has collected bank-specific information at different levels of aggregation on Basel II RWAs, capital requirements and risk parameters. The data are extracted from the national reporting frameworks of member jurisdictions and submitted to the Basel Committee Secretariat in standardised reporting templates.

The Committee decided to use the CMG data as the basis for analyses for several reasons:

- First, the CMG data set contains more granular information on Basel II RWAs and associated risk parameters than is available in alternative sources such as Pillar 3 disclosures. The granularity of CMG data varies across bank submissions. Nevertheless, a typical CMG bank submission will include Basel II information along the following dimensions: EAD, RWA, EL, PD and LGD by portfolio; post-CRM/CCF EAD; the split between defaulted and non-defaulted exposures; EAD and RWAs by approach used (partial use, FIRB, AIRB); and distinctions between corporate, retail, bank, sovereign, counterparty, equity, securitisation and trading book portfolios. The availability of EAD data allows the calculation of RWA density, ie RWAs divided by EAD, instead of dividing RWAs by total assets as is the case in most private sector studies.
- Second, because CMG data are compiled into a common reporting framework (the CMG template), it is far easier to aggregate the data into uniformly defined risk measures than if the Basel Committee were to obtain data directly from existing reporting frameworks.
- Third, the use of reported exposure numbers helps avoid the need for various ad hoc adjustments made in other studies that are based on disclosed financial information.
- Fourth, the scope of the CMG data tends to be broader, in terms of both the number of banks and the number of jurisdictions covered, than the samples used in other studies (typically compiled from Pillar 3 disclosures).<sup>59</sup>

<sup>59</sup> The CMG dataset currently covers 57 large, internationally active banking organisations and 45 non-internationally active banking organisations in 15 jurisdictions. The jurisdictions included (number of banks in parenthesis) are Australia (4), Belgium (5), Canada (6), France (6), Germany (23), Italy (6), Japan (11), Luxembourg (1), the Netherlands (6), South Africa (4), Spain (6), Sweden (9), Switzerland (2), the United Kingdom (8), and the United States (5).

## Annex 3: Outcome of analysis based on CMG data (30 Jun 2012)

Share of credit exposures (EAD) across asset classes (%)						Table 1
	Mean	Median	Minimum	25th Percentile	75th Percentile	Maximum
<b>Corporate</b>	<b>27</b>	<b>26</b>	<b>0</b>	<b>15</b>	<b>33</b>	<b>64</b>
<b>Retail</b>	<b>23</b>	<b>25</b>	<b>0</b>	<b>13</b>	<b>45</b>	<b>80</b>
Partial Use	21	23	0	8	40	83
Sovereign	14	5	0	0	15	48
Bank	7	6	0	0	10	78
Securitisations	3	2	0	0	3	66
Other Assets	2	0	0	0	2	25
Equity	1	0	0	0	1	5
Funds	1	0	0	0	0	22
Receivables	0	0	0	0	0	7
Related Entities	0	0	0	0	0	3

The Committee also evaluated the extent to which Basel II risk measures are correlated with other risk measures. There are strong positive correlations between banks' PD estimates and historical default rates<sup>60</sup> for both the corporate and retail asset classes (Charts 1 and 2), although there are also significant outliers on either side of the best fit lines which suggests that some banks' PD estimates may not be representative of their actual default experiences.<sup>61</sup>

Chart 1: Corporate Exposure PD<sup>62</sup> versus historical Default Rate

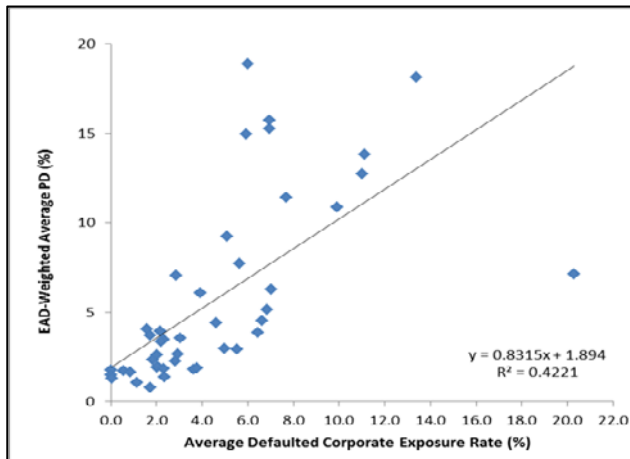
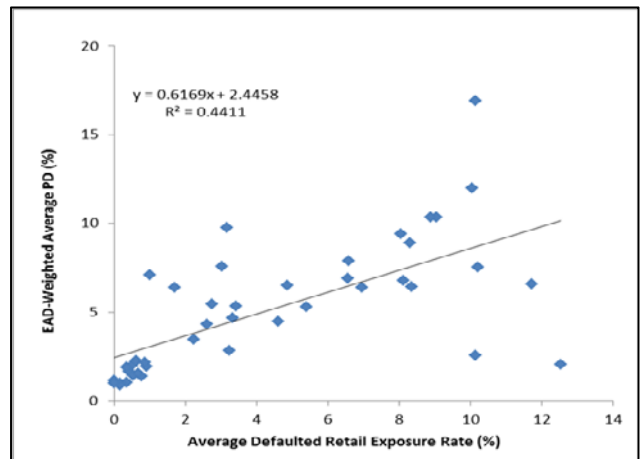


Chart 2: Retail Exposure PD<sup>63</sup> versus historical Default Rate



A similar analysis undertaken for banks' LGD estimates and a proxy for historical realised LGDs (ie historical loss rates divided by historical default rates)<sup>64</sup> reveals a weak positive correlation for retail exposures but no clear relationship for corporate exposures (Charts 3 and 4). The lack of a clear relationship may be the result of inadequately comparable data on losses, as loss recognition practices vary across jurisdictions.

<sup>60</sup> Historical loan default data were obtained or approximated for 54 CMG banks. The average default rate was generally calculated using quarterly or semi-annual balance observations from 4Q 2008 to 2Q 2012. For some banks, data were only available for a portion of this time span covering the more recent periods.

<sup>61</sup> It is also possible that the default experience in the relatively short sample period covered is not representative of long-run experience.

<sup>62</sup> Weighted-average PDs including defaulted exposures.

<sup>63</sup> Weighted-average PDs including defaulted exposures.

<sup>64</sup> Proxies of realised LGDs, which require information on historical loss and default rates, were successfully calculated for 35 CMG banks. Averages were generally calculated using quarterly or semi-annual loss rate observations from 4Q 2008 to 2Q 2012. As with default rates, loss rate data for some banks was only available for a portion of this time span covering the more recent periods.

Chart 3: Corporate Exposure LGD versus realised corporate LGD

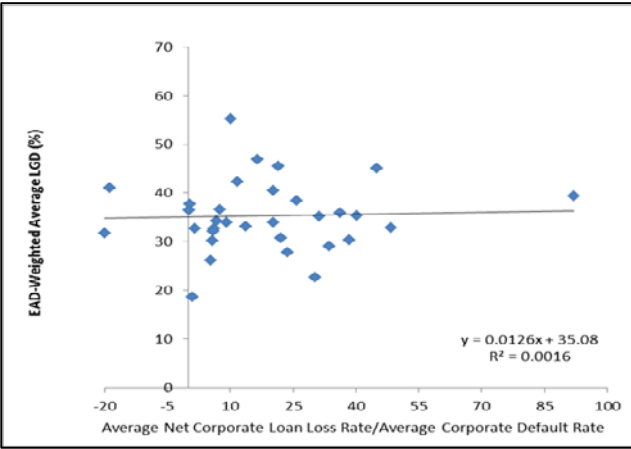
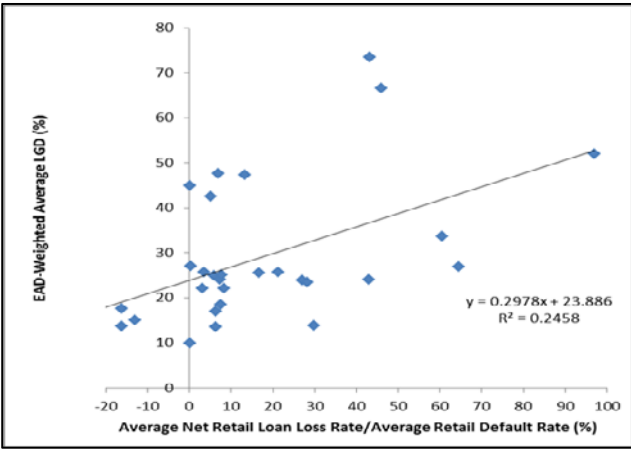


Chart 4: Retail Exposure LGD versus realised retail LGD



Finally, the Committee found weak positive correlations between banks’ average risk weights and certain market risk measures, including banks’ stock return volatilities and debt ratings ( Charts 5 and 6).

Chart 5: Stock volatility versus total RWA density rank

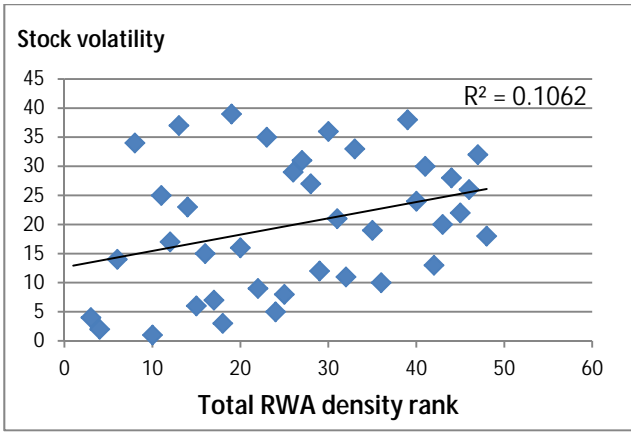
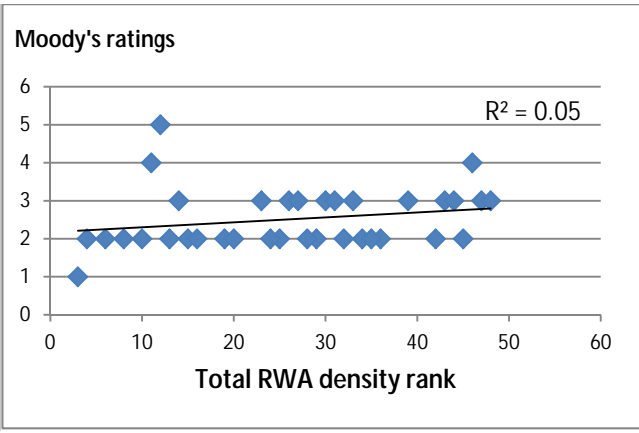


Chart 6: Moody’s ratings versus total RWA density rank<sup>65</sup>



<sup>65</sup> The numerical rating grades on the vertical axis correspond to Moody's ratings of Aaa, Aa1, Aa2, Aa3, etc.

EAD-weighted PDs (including defaulted exposures)

Table 2

	Mean	5th percentile	25th percentile	75th percentile	95th percentile	Number of portfolios
Corporate	5.1	1.0	2.5	7.9	17.5	86
Retail	4.8	1.1	1.8	6.1	11.1	87
Sovereign	0.3	0.0	0.0	0.5	3.4	65
Bank	0.7	0.1	0.1	0.8	2.7	75

EAD-weighted PDs (excluding defaulted exposures)

Table 3

	Mean	5th percentile	25th percentile	75th percentile	95th percentile	Number of portfolios
Corporate	1.4	0.5	1.0	2.1	4.4	88
Retail	1.9	0.4	0.9	2.4	4.2	88
Sovereign	0.1	0.0	0.0	0.1	0.6	67
Bank	0.2	0.1	0.1	0.3	0.6	77

EAD-weighted LGDs

Table 4

	Mean	5th percentile	25th percentile	75th percentile	95th percentile	Number of portfolios
Corporate	35.9	18.3	31.0	41.2	45.3	85
Retail	31.1	10.3	17.1	35.7	57.7	87
Sovereign	30.0	5.3	14.3	45.0	45.1	65
Bank	30.2	16.5	25.3	39.9	48.6	75

EAD-weighted Maturity

Table 5

	Mean	5th percentile	25th percentile	75th percentile	95th percentile	Number of portfolios
Corporate	2.5	1.7	2.4	2.7	3.3	85
Sovereign	2.5	1.0	1.9	2.9	4.1	65
Bank	1.9	0.5	1.5	2.5	2.9	75



Analysis of relationship between Partial Use share and Risk Weights

Table 6

Relationship evaluated	Including observations with 100% Partial Use		Excluding observations with 100% Partial Use	
	Coefficient (significance)	R <sup>2</sup>	Coefficient (significance)	R <sup>2</sup>
Overall risk weight and partial use share	0.07 ( )	.0123	0.07 ( )	.0123
Corporate risk weight and partial use share	0.44 (***)	.4194	<b>0.42 (***)</b>	.2367
Retail risk weight and partial use share	0.47 (***)	.5934	<b>0.63 (***)</b>	.3962
Sovereign risk weight and partial use share	−0.04 (***)	.3709	<b>−0.03 (*)</b>	.1317
Bank risk weight and partial use share	0.08 (**)	.1461	−0.04 ( )	.0245