An economic capital model integrating credit and interest rate risk in the banking book

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ABSTRACT

Banks often measure credit and interest rate risk in the banking book separately and then add the risk measures to determine economic capital. This approach misses complex interactions between the two risk types. We develop a framework where these risks are analysed jointly. Since banking book positions are generally not marked to market, our model is based on book value accounting. Our simulations show that interactions matter, and that ignoring them leads to risk overstatement. The magnitude of the errors depends on the structure of the balance sheet and on the repricing characteristics of assets and liabilities.

1. Introduction

"The Committee remains convinced that interest rate risk in the banking book is a potentially significant risk which merits support from capital" (Basel II, Paragraph 762, Basel Committee, 2006).

The view expressed by the Basel Committee in the Basel II capital accord receives strong support from the data. According to industry reports, interest rate risk is after credit risk the second most important risk when determining economic capital for the banking book (see IFRI-CRO, 2007). However, no unified economic capital model exists which integrates both risks in a consistent fashion. Therefore, regulators and banks generally analyse these risks independently from each other and derive total economic capital by some rule of thumb. Indeed, the most common rule arguably consists in simply "adding up". A serious shortcoming of this procedure is that it obviously fails to capture the interdependencies between both risks. For example, the literature has shown consistently that interest rates are a key driver of default frequencies, i.e. interest rate risk drives credit risk. And as we will show, credit risk also drives interest rate risk in the banking book.

This raises several questions: what is the optimal level of economic capital if the interdependencies are captured? Do additive rules provide a good approximation to the true integrated capital? More importantly, is the former approach always conservative or can both risks compound each other in some circumstances? In order to answer these questions, we derive integrated economic capital for a traditional banking book and we compare it to economic capital set against credit as well as interest rate risk when interdependencies are ignored. We show that this is only possible by using an economic capital model, developed in this paper, which consistently integrates credit and interest rate risk taking account of the complex repricing characteristics of asset and liabilities.

Traditionally it would be argued that, if a portfolio is exposed to two imperfectly correlated risks, the sum of capital buffers set against the two ought to be larger than the (true) underlying economic capital level. Unfortunately, this is not generally the case. Breuer et al. (2010) discuss this problem in the context of market and credit risk assessment for the banking and trading book. They show theoretically as well as empirically that under some circumstances the risk measure of the total portfolio (i.e. the bank) can be higher that the sum of the risk measures set for the two books independently. This possibility can arise whenever market and credit risk are not "separable", in the sense that some exposures depend on both credit and market risk factors.
This result has strong implications for risk management, as regulators and practitioners typically set capital against credit and interest rate risk independently, and then obtain a measure of total capital by simply adding these up (we label this “simple economic capital” for convenience). If risks were separable and a sub-additive measure of risk is used, this procedure would always deliver an upper bound in comparison with the correct underlying capital. However, as we argue below, credit and interest rate risk interact in a complex, non-linear way. Hence, simple economic capital may actually turn out to be lower than “integrated economic capital”, i.e. the capital level implied by a consistent, joint analysis of credit and interest rate risk.

The conceptual contribution of the paper is to derive an economic capital model which takes account of credit and interest rate risk in the banking book. Although new accounting standards allow banks to use the fair value option for some securities, most assets and liabilities in the banking book are valued at book value as banks hold them to maturity. Under book value accounting, profits and losses are accounted for only when they materialise, i.e. what matters are realised net cash flows and not changes in the economic value. The way we set capital against credit and interest rate risk individually is fully in line with standard practices. The credit risk component is based on the same conceptual framework as Basel II and the main commercially available credit risk models. Interest rate risk, on the other hand, is captured by earnings at risk, the approach banks commonly use to measure this risk type (see Basel Committee, 2008). In contrast to standard models, however, we integrate credit and interest rate risk using the framework proposed by Drehmann et al. (2010), henceforth DSS, taking into account all relevant interactions between both risks. These are threefold: (a) both risks are driven by a common set of risk factors; (b) interest rates are an important determinant of credit risk; and (c) credit risk impacts significantly on net interest income. These interactions can be illustrated with a simple example. Consider a macroeconomic shock that shifts the yield curve upwards and depresses asset prices, thereby increasing credit losses. If the bank borrows short and lends long, interest margins are compressed and net interest income falls, which generates a further fall in net profits. However, over time the bank can progressively reprice its exposures taking into account higher interest rates and credit risk. The repricing process boosts net interest income, offsetting the effects of higher funding costs and higher default rates. DSS analyse a similar stress scenario, showing that profits drop substantially at the beginning but start to recover after about one year, even before defaults reach their peak.

In this paper we show that changes in net interest income can be decomposed into two components: the first one captures the impact of changes in the yield curve, while the second accounts for the crystallisation of credit risk, which implies a loss of interest payments on defaulted loans. As coupons only default in conjunction with the underlying loans, the latter component can be integrated easily into a standard credit risk model. Conditionally on the state of the macroeconomy, these two sources of income risk are independent. This important insight significantly simplifies their aggregation. It also underlines that conditioning on the macroeconomic environment is crucial for an economic capital model aiming to integrate credit and interest rate risk.

Assuming a one year horizon, we apply our model to a stylised bank and compare the (true) integrated economic capital to simple economic capital, i.e. the sum of capital set separately against credit and interest rate risk. Economic capital is set in line with current market and regulatory practices as “the amount of capital a bank needs to absorb unexpected losses” (Basel Committee, 2008, p. 9). In contrast to Breuer et al. (2010), who show that simple economic capital may not adequately reflect the underlying risks, we find that this is unlikely to be the case for a traditional banking book. Obviously, our conclusion may not extend to institutions that face a wider range of risks or use mark-to-market accounting. Nonetheless, for all the portfolios we analyse we find that simple economic capital exceeds integrated economic capital, even though the quantitative difference depends on the structure and repricing characteristics of the bank’s portfolio.

The remainder of the paper is structured as follows. Section 2 provides a short overview of the literature. In Section 3 we derive the integrated economic capital model. Section 4 discusses our implementation and Section 5 presents the results. Section 6 undertakes some sensitivity tests. Section 7 concludes.

2. Literature

There is by now a large and well known literature on economic capital models for credit risk (for an overview see e.g. McNeil et al., 2005). Most models are based on the idea that there is one or a set of common systematic risk factors which drive default rates of all exposures, but that conditional on a draw of systematic risk factors, defaults across exposures are independent. Our approach to credit risk modelling follows this tradition. However, contrary to most models, we condition credit risk and the yield curve on a common set or systematic risk factors. Furthermore, we account for the loss in coupon payments if assets default.

In contrast to credit risk, no unified paradigm has yet emerged on how to best measure interest rate risk in the banking book (e.g. see Kuritzkes and Schueremann, 2007). The Basel Committee points to this as an important reason why interest rate risk in the banking book is not treated in a standardised fashion in the Basel II capital framework (see Paragraph 762, Basel Committee, 2006). Interest rate risk in the banking book can either be measured by earnings at risk or using an economic value approach. The latter measures the impact of interest rate shocks on the value of assets and liabilities, whereas the former looks at the impact of the shocks on the cashflow generated by the portfolio (i.e. a bank’s net interest income). Some banks have moved towards an economic value perspective, but this paper follows the traditional earnings at risk approach which is still heavily used in the industry and for regulatory purposes (see Basel Committee, 2008).

From the perspective of an integrated risk management framework, standard interest rate risk analysis has an important drawback: implicitly, these methods assume that shocks to the risk-free yield curve have no impact on the credit quality of assets. But clearly this assumption does not hold: interest rates risk and credit risk are highly interdependent and, therefore, need to be assessed jointly.

Jarrow and Turnbull (2000) are among the first to show theoretically how to integrate interest rate (among other market risks) and credit risk. Their theoretical framework is backed by strong empirical evidence that changes in interest rates impact on the credit quality of assets (e.g. see Carling et al., 2007). However, if papers integrate both risks, they look at the integrated impact of credit and interest rate risk on assets only, for example by modelling bond portfolios without assessing the impact of interest and credit risk on liabilities or off-balance sheet items with different repricing characteristics. Barnhill and Maxwell (2002) measure credit and market risk for the whole portfolio of banks. They take a mark-to-market perspective but ignore one of the most important sources of interest rate risk – repricing mismatches between assets and liabilities as the most important source of interest rate risk.
and liabilities. Whilst we do not take a mark-to-market perspective, our work focuses on the latter effect, providing a thorough description of how a bank’s maturity structure and pricing behaviour affects its risk profile.

While we use the framework of DSS to derive net interest income, our implementation differs. For their stress test, DSS use a structural macroeconomic model which cannot be easily simulated. Instead, we use a two-country Global Vector Autoregression (Pesaran et al., 2004) which allows us to undertake stochastic simulations and therefore enables us to derive the full net profit distribution. Furthermore, in contrast to DSS, we look at both expected and unexpected credit risk losses.

So far there has been a limited discussion of how interdependencies across risks impact on economic capital. Decomposing net income into its components (i.e. market, credit, interest rate risk in the banking book, operational and other risks) and computing returns on risk weighted assets, Kritzkes and Schuermann (2007) find that interest rate risk in the banking book is after credit risk the second most important source of financial risks. Furthermore, they show that there are diversification benefits between risks.

Significant diversification benefits are also found in studies which use simple correlations between different risks (Kritzkes et al., 2003 or Dimakos and Aas, 2004). However, as Breuer et al. (2010) point out, these papers implicitly assume that risks are separable, which in the case of market (and hence interest rate risk) and credit risk is not necessarily true. As already discussed in the introduction, the authors find that total risk can be under- as well as overestimated if market and credit risk are wrongly assumed to be separable.

This is consistent with the findings in Kupiec (2007). The paper extends a single-factor credit risk model to take into account stochastic changes in the credit quality (and hence the market value) of non-defaulting loans. The value of the resulting portfolio is a non-separable function of market and credit risk factors. The author compares an integrated capital measure to additive measures calculated under a range of credit and market risk models, and finds that no general conclusion can be reached on whether additive rules under- or overestimate risk.

It is worth stressing that the diversification issue should ideally be examined within a model that integrates all relevant risks, and that such a model is not available to date. For instance, Kupiec (2007) or Breuer et al. (2010) focus on the asset side, abstracting from any issues related to maturity mismatch and net interest income volatility, whereas in this paper we model these in detail but do not consider changes in the economic value of the portfolio. Therefore, the literature can currently only provide partial answers to the general question of when and why additive rules can underestimate risk.

3. The framework

Throughout the framework discussion, we assume that the bank holds a portfolio of assets $A = \{A^1, \ldots, A^N\}$. Each exposure $A^i$ has a specific size, a time to repricing $b^i$, a default probability $PD^i(X)$, loss given default $LGD^i$, and coupon rate $C^i$. For the derivation of the one period set-up in Section 3.1 we assume fixed coupons $C^i$; this assumption is relaxed in Section 3.2. Interest rates and defaults are driven by a common set of systematic risk factors $X$, that follow a generic probability distribution $F$. Following the literature, we also assume that conditional on $X$, defaults across different assets $A^i$ are independent.

The bank is funded by $M$ liabilities $L = \{L^1, \ldots, L^M\}$. Each liability $L^j$ falls into a repricing bucket $b^j$ and pays a coupon rate $C_j^i$. Coupon rates are again assumed to be fixed in the single period framework but endogenous in the multi-period set-up. All assets and liabilities are held in the banking book, using book value accounting.

3.1. Single period framework

In a standard portfolio model (e.g. see McNeil et al., 2005), the total loss $L$ of the portfolio is a random variable and can be characterised by

$$L(X) = \sum_{i=1}^{N} \delta(X)A^iLGD^i$$

where $\delta(X)$ is a default indicator for asset $i$ taking the value 1 with probability $PD^i(X)$ and the value 0 with probability $(1-PD^i(X))$. We assume conditional independence. Therefore, conditional on the state of systematic risk factors $X$, the default indicators $\delta(X)$ are i.i.d. Bernoulli random variables. Hence, our set-up is in the tradition of Bernoulli mixture models. It has been shown that all standard industry models such as CreditRisk + or CreditPortfolioView, but also Basel II, can be formulated in this fashion (e.g. see McNeil et al., 2005). Note, that generally these models, and in particular Basel II, do not take changes in the mark-to-market value into account. The models only differ in their assumptions on the distribution of the systematic risk factors, the mapping between risk factors and PDs, and whether they are solved analytically or numerically.

Incorporating interest income in this framework is straightforward. Net interest income is simply interest payments received on assets minus interest payments paid on liabilities. Given our assumption of fixed coupon rates, the only stochastic component of net interest income in the one period set-up is whether assets default of not. Take an asset $A^i$. If no default occurs, the cash flow contribution to interest income is $CA^i$. In case of default, the cash flow contribution is only $(1-LDG^i)CA^i$ as we assume that coupon payments can be partially recovered with the same recovery rate $(1-LDG^i)$ as the principal. Total realised net interest income $NI^i$ is therefore

$$NI^i = \sum_{i} [CA^i - \delta(X)LGD^iCA^i] - \sum_{j} C_j^i$$

As can be seen from Eq. (2), realised net interest income can be decomposed into a component $NI$ which excludes the effect of default ($NI = \sum_i CA^i - \sum_i C_j^i$) and a term which sums over coupon losses due to crystallised credit risk. Given that coupon rates are pre-determined, $NI$ is not stochastic. However, since coupons only default when the underlying asset defaults, the second random component can be incorporated into a redefined credit loss distribution $L^i$:

$$L^i(X) = \sum_{i} \delta(X)(1+C^i)A^iLGD^i$$

The unconditional distributions of both $L$ and $L^i$ is then derived numerically. Ultimately we are interested in net profits $NP(X)$ which are the sum of credit risk losses and net interest income:

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1 The papers look at a maturity mismatch of ± one year and conclude that this is important. But ± one year is clearly too simplistic to capture the full impact of the maturity mismatch on the riskiness of banks. 4 This is the standard assumption used in credit risk models implemented for day to day risk management, even though recent research has shown that this assumption does not necessarily hold (e.g. see Egloff et al., 2007).
\[ NP(X) = RN(X) - L(X) = NI - L^*(X) \]  

Since \( NI \) is non-stochastic, only \( L^* \) introduces randomness into \( NP \). Therefore, the net profit distribution is identical to the distribution of \( -L^* \) bar a mean shift of the size of \( NI \) (see Fig. A1 in the Annex for a graphical representation).

Standard economic capital models for credit risk assume that the expected loss is covered by income, which implies zero expected profits. As an aside, it is interesting to observe that this condition holds exactly in our model if (a) the bank is fully funded by liabilities, (b) all liabilities pay the risk-free rate, (c) assets and liabilities have a repricing maturity of one period, and (d) assets are priced in a risk-neutral fashion.\(^5\) As will become apparent from our simulation results, any departure from this simple case will imply non-zero (typically positive) net profits.

### 3.2. The multi-period framework

In order to implement the model dynamically, we need to introduce explicit assumptions on the behaviour of banks and customers:

(i) Depositors are passive: once deposits mature, depositors are willing to roll them over maintaining the same repricing characteristics.

(ii) The bank does not actively manage its portfolio composition: if assets mature or default, the bank continues to invest into new projects with the same repricing and risk characteristics as the matured assets. At the end of each period, the bank also replaces defaulted assets with new assets which have the same risk and repricing characteristics.

These assumptions are essential to ensure that the bank’s balance sheet balances at each point in time. Whilst this is a fundamental accounting identity which must hold, risk management models often ignore it as profits and losses are not assessed at the same time. This is one crucial innovation in the framework of DSS. Assumption (i) implies that the volume and source of deposits does not change over time. Assumption (ii) is often used in practice by risk managers, who call this “ever-greening” the portfolio. In case of default, the new asset is funded by reinvesting the recovery value of the defaulted loan and the remainder out of current profits or shareholder funds. We assume that any positive profits are held in cash until the end of the year and are not invested in additional loans.\(^4\) This stock of cash is used to buffer negative net profits. Whenever the buffer is not sufficient and capital falls below initial levels, we assume that shareholders inject the necessary capital at the end of the quarter. Taken together, our assumptions imply that at the beginning of each period the overall portfolio is the same in terms of risk and repricing characteristics. Clearly, our behavioural assumptions are to a certain degree arbitrary. But we restrict ourselves to simple, commonly used behavioural rules rather than re-optimising the bank’s portfolio in a mean-variance sense in each period as this would be beyond the scope of this paper.

At the beginning of the simulations the bank starts with a portfolio \( A_0 = \sum_i A^i_0 \) and \( L_0 = \sum_j L^j_0 \). Initial coupon rates for assets \( C^i_0(X_0) \) and liabilities \( C^j_0(X_0) \) are priced based on macroeconomic conditions \( X_0 \) at time 0. At the beginning of period 1 a shock hits the economy changing the macroeconomic conditions to \( X_1 \), which can already be taken into account when the bank re-prices all assets and liabilities with a time to re-pricing of 1. After re-pricing, credit risk losses are realised; then interests on assets and liabilities are paid, and time-1 net profits are calculated. Finally, the bank replaces the defaulted assets and re-invests matured assets and liabilities. This sequence is repeated for each quarter in the simulation. Note, however, that a different fraction of the portfolio is repriced in each period, as individual assets and liabilities have different times to re-pricing (see DSS for a detailed illustration of the dynamics of the pricing process).

#### 3.2.1. NI in the multi-period framework

In a dynamic set-up, coupons change over time reflecting movements in the yield curve and changes in the credit quality of the exposures; hence, \( NI \) is itself stochastic. The modelling approach is in line with DSS and it is summarised in Appendix A. Essentially, each asset (liability) can be repriced at a particular point depending on its time to re-pricing \( b_i \) (\( b_j \)). Conditional on a realisation of \( X_t \), total net interest income \( NI_t(X_t) \) in period \( t \) can therefore be written as

\[ NI_t(X_t) = NI^A_t(X_t) - NI^L_t(X_t) \]  

with

\[ NI^A_t(X_t) = \sum_{i=1}^{N} \sum_{t=0}^{T} \int C^i_t(X_t) A^i_t \]  

\[ NI^L_t(X_t) = \sum_{j=1}^{M} \sum_{t=0}^{T} \int C^j_t(X_t) L^j_t \]  

Eq. (5) sums across coupon incomes from different assets which have been repriced at different periods. Each exposure \( A^i \) has been (re)priced in some period \( p^i < t \), and earns a coupon \( C^i_{p^i}(X_{p^i}) \) which was set based on the macroeconomic conditions that prevailed at time \( p^i \). The indicator function \( I_p \) (which is equal to one for \( p = p^i \) and zero otherwise) identifies the point in time at which the repricing took place. Note that assets which had an initial time to repricing \( b_i \) have not been repriced, so they still earn coupon rates \( C^i_0(X_0) \).\(^7\) Eq. (6) looks at the liability side; the interpretation is analogous to Eq. (5).

Eqs. (5) and (6) are at the heart of the model. They imply that for every macro scenario we need to track coupon rates for all asset and liability classes with different repricing maturities. Coupon rates in turn are set in different time periods and depend on the prevailing and expected macro factors at that point in time. In comparison to standard credit risk models, this increases the computational complexity enormously.

#### 3.2.2. The multi-period profit and loss distribution

Given our timing assumptions, at every period \( t \) banks observe the latest risk factor realisation \( X_t \) before pricing their assets. Conditional on \( X_t \), \( NI_t(X_t) \) is non-stochastic; therefore, we can apply the framework developed in Section 3.1 on an iterative basis. This is a crucial insight of our framework as it allows us to disentangle interest income and credit risk losses including defaulted coupons.

In each period, \( NI \) is determined by Eq. (4), and losses due to the default of coupons and principals are determined by Eq. (1). Note that coupon rates between periods may change and need to be

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\(^5\) A proof of this claim can be found in the working paper version (see Alessandri and Drehmann, 2010). We also implemented this simple example (fully matched bank, risk neutral pricing, one-quarter horizon) in our simulations, confirming that mean net profits are indeed zero. Results are available upon request.

\(^6\) By holding profits in cash the bank foregoes potential interest payments. However, given the one-year horizon, these are immaterial. As a sensitivity test we replicated our baseline results under the assumption that profits earn the risk-free rate of return, and the changes turned out to be negligible. Details are available upon request.

\(^7\) For example in period 4, all assets which had initially a time to repricing \( b_i > 4 \) continue to carry the initial coupon rates (i.e. they have \( t_i = 1 \)). Assets with repricing maturities of less than 4 periods have been repriced prior to or at the beginning of period 4. In particular, assets with \( b_i = 1,2,4 \) have been repriced in period \( p^i = 4 \), so for all these assets \( t_i = 1 \), whereas assets with \( b_i = 3 \) were last repriced in period \( p^i = 3 \) and hence \( t_i = 1 \).
incorporated into (19) in the dynamic set-up. Therefore credit risk losses including defaulted coupons conditional on $X$ at time $t$ are

$$L_t^i(X_t) = \sum_{i=1}^{N} \sum_{t=0}^{T} \int_{p_i}^{p_i} \delta(X_t)(1 + C_i(X_t))A_{tL}G_d$$  \hspace{1cm} (7)$$

where $i$ and $\delta$ are again indicator functions, $i = 1$ for $t = p_i$, when asset $A_i$ has been repriced the last time prior to time $t$, and $i = 0$ otherwise. $\delta(x) = 1$ if asset defaults at time $t$, and $\delta(x) = 0$ otherwise. The interpretation is in line with Eqs. (5) and (6). Note, however, that the default indicator does not depend on the repricing maturity but only on credit conditions at time $t$. We can again define net profits as $NP_t(X_t) = N_t(X_t) - L_t^i$, and calculate total profits over the whole horizon $T$ as:

$$NP_T(X_T) = \sum_{t=1}^{T} NP_t(X_t) = \sum_{t=0}^{T} \left(N_t(X_t) - L_t^i(X_t)\right)$  \hspace{1cm} (8)$$

where $X_T = \{x_0, x_1, \ldots, x_T\}$ denotes a history of risk factor realisations. The specific implementation is discussed in the next section, but the mechanism follows our time line. In each period, we first draw $X_t$, then determine $N_t$, simulate defaults of individual assets and coupons and finally calculate $NP_t$. After reinvestment, this process is repeated for the next quarter and so on up to time $T$. In the end we sum across all quarters and repeat the simulation. Note that our horizon of interest is one year; since $T = 4$ throughout the analysis, we drop the time index $T$ in the remainder of the paper.

### 3.3. Economic capital

As discussed in the introduction, in line with current market and regulatory practices, we set the level of capital such that it equals the amount a bank needs to absorb unexpected losses over a certain time horizon at a given confidence level (Basel Committee, 2008, or Kuritzkes and Schuermann, 2007). In our framework, unexpected losses can arise because of credit risk or adverse interest rate shocks.

For credit and interest rate risk, we follow standard convention and measure unexpected losses as the difference between the Value at Risk (VaR) and expected losses. More precisely, the VaR of the credit risk loss distribution $VaR_{EC}$ at a confidence level $\gamma(0, 1)$ is defined as the smallest number $l$ such that the probability of $L$ exceeding $l$ is not larger than $(1 - \gamma)$:

$$VaR_{EC} = \inf \{l; P(L \geq l) \leq (1 - \gamma)\}$$  \hspace{1cm} (9)$$

For risk management purposes the confidence level is generally high with $y > 0.9$. We set economic capital against credit risk $EC_{EC}$ at the confidence level $\gamma(0, 1)$ so that it covers the difference between expected and unexpected losses up to $VaR_{EC}$. Or formally

$$EC_{EC} = VaR_{EC} - E(L)$$  \hspace{1cm} (10)$$

In analogy with (9), we define the VaR of the $NI$ distribution $VaR_{NI}$ at a confidence level $\gamma(0, 1)$ as the smallest number $n$ such that the probability of $NI$ exceeding $n$ is not larger than $(1 - \gamma)$:

$$VaR_{NI} = \inf \{n; P(NI \geq n) \leq (1 - \gamma)\}$$  \hspace{1cm} (11)$$

$NI$ provides positive contributions to net profits, so we are interested in the left tail of the distribution. Therefore $z$ is in this case below or equal to 0.1. Given that the focus is on the left tail, economic capital $(EC_{EC}^{1-\gamma})$ is meant to cover unexpectedly low $NI$ outcomes at the confidence level $(1 - \gamma)$:

$$EC_{EC}^{1-\gamma} = E(NI) - VaR_{NI}$$  \hspace{1cm} (12)$$

Given this definition, economic capital set at the 99% confidence level covers all unexpected low outcomes of $NI$ between the $VaR_{NI}$ at the 1% level and expected $NI$. Note that $VaR_{NI}$ and $EC_{EC}$ do not incorporate defaulted coupons. As we noted above, these are an important part of the analysis and they can be accounted for equivalently in the income calculation (2) or in the credit risk loss calculation (19). We follow the first route and construct $VaR$ and $EC$ statistics for realised net interest income $RNI$, which incorporates the loss of payments on defaulted assets. The definitions of $VaR_{RNI}$ and $EC_{RNI}$ are analogous to Eqs. (11) and (12).

Ultimately, we are interested in risk measures for the net profit distribution. Risk managers obviously do not focus on the right tail of this distribution, which constitutes the up-side risk for a bank, but on the left tail. In line with $VaR_{RNI}$, we define the VaR of the net profit distribution $VaR_{NP}$ at a confidence level $\gamma(0, 1)$ as the smallest number $np$ such that the probability of $NP$ exceeding $np$ is not larger than $(1 - \gamma)$:

$$VaR_{NP} = \inf \{np; P(NP > np) \leq (1 - \gamma)\}$$ \hspace{1cm} (13)$$

Mechanically we could set capital against net profits such that it buffers all unexpected low outcomes; i.e. we could set it as the difference between $E(NP)$ and $VaR_{NP}$. Mathematically this definition would make sense. Economically, however, it does not because it implies that the bank also holds capital against low but positive profits, even though banks hold, as discussed above, capital to buffer (unexpected) losses. To clarify this, say a bank manages its capital to a 95% confidence level and $VaR_{NP}^{0.95} > 0$. Such a bank would not hold any capital as it knows that it makes positive profits with a 95% likelihood. Even if it manages capital to a confidence level of 99% and $VaR_{NP}^{0.99} < 0$, the bank would not set capital as the difference between $E(NP)$ and the VaR because it does not make sense to “buffer” positive profits. Insofar as the bank only holds capital against net losses, a more sensible definition of the economic capital $EC_{EC}^{1-\gamma}$ at a confidence level $(1 - \gamma)$ is

$$EC_{EC}^{1-\gamma} = \left\{ \begin{array}{ll} 0 & \text{if } VaR_{NP} \geq 0 \\ -VaR_{NP} & \text{if } VaR_{NP} < 0 \end{array} \right. $$  \hspace{1cm} (14)$$

The intuition behind Eq. (14) is illustrated in Fig. A1 in the Annex. Here $VaR_{NP} > 0$ at a confidence level $(1 - \gamma)$, so no capital is needed. Using a higher confidence level $(1 - \gamma)$ some unexpected negative net profits (i.e. net losses) can materialise and the bank would set capital to buffer the possible negative outcomes.

As discussed in the introduction, we are ultimately interested in assessing whether setting economic capital in a naive fashion by adding economic capital against credit risk and economic capital against net interest rate risk (including defaulted coupons) provides a conservative bound in comparison with setting capital against net profits. We assess this by looking at the following measure for confidence level $\gamma$

$$M_{EC} = \frac{(EC_{EC}^{1-\gamma} + EC_{EC}^{\gamma}) - EC_{NP}}{(EC_{EC}^{1-\gamma} + EC_{EC}^{\gamma})}$$  \hspace{1cm} (15)$$

The larger $M_{EC}$, the more conservative simple economic capital is. Conversely, if $M_{EC}$ is negative then simply adding up the two capital measures independently would underestimate the risk of the total portfolio.

In our framework, $EC_{NP}$ covers negative net profits (i.e. net losses) rather than looking at the difference between expected net profits and unexpected net profits as $EC_{RNI}$ and $EC_{EC}$. This

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9 It is well known that VaR is not a coherent risk measure. However, expected shortfall is not coherent in our set-up either as credit and interest rate risk interact in a non-linear fashion. Therefore we only report economic capital numbers based on VaR measures. The insights from all results remain when using expected shortfall instead. Results are available on request.
is economically sensible, because profit fluctuations have a direct impact on bank capital independently of whether they are expected or not. With perfect competition and risk-neutral pricing, average profits would be zero and the difference would not be material. However if banks earn rents (for example by pricing customer deposits below the risk-free rate, as we can observe empirically) expected profits are positive, which increases $M_{EC}$. In other words, rents may introduce a further wedge between “simple” and “integrated” economic capital. We maintain that $M_{EC}$ is the most appropriate measure in this context, but to control for this issue we also provide an alternative measure $M_2$ that takes into account the mean of the net profit distribution:

$$M_2^* = \frac{(EC_{CR} + EC_{BN}) - \left(E(NP) - Var^{1/2}(NP)\right)}{(EC_{CR} + EC_{BN})} \quad (16)$$

Given that we model a banking book, $EC_{CR}$ and $EC_{BN}$ do not take account of changes in the mark-to-market valuations of the exposures; hence, they do not capture aspects of, and interactions between, credit and interest rate risk which arise when assets are marked to market (we briefly discuss this in the conclusions). It can also be argued that $EC_{CR}$ and $EC_{BN}$ do not fully disentangle credit and interest rate risk, in the sense that the former incorporates the effect of higher interest rates on default probabilities and the latter the effect of higher (actual or expected) credit risk on income. These issues should be certainly kept in mind throughout the discussion of our results. The key point, though, is that our framework represents a plausible description of how current capital models for the banking book capture these risks. As already discussed, the current regulatory approach to credit risk and the commonly used “earnings at risk” approach to interest rate risk do not make changes in market valuations into account. Furthermore, some credit risk models include a set of macroeconomic risk factors and hence capture (directly or indirectly) some of the links between interest rates and credit risk. This is for instance the case for CreditPortfolioView (Wilson 1997a,b), the classic example of such an economic capital model. To the extent that our $EC_{CR}$ and $EC_{BN}$ definitions reflect limitations and ambiguities that are common to many widely used risk management tools, the model should provide a plausible benchmark for our “simple economic capital” setting. Our pricing model represents a departure from standard modelling practices. Most interest rate risk models do not take account of the possible repricing of assets beyond changes in the risk-free rate. Hence, by modelling endogenous spreads we add a layer of realism and complexity to the analysis. However, in line with standard approaches to model interest rate risk, we also undertake a sensitivity test where all spreads are excluded (see Section 6.1).

4. Implementation

Most quantitative risk management models currently used can be described as a chain starting with shocks to systematic risk factors feeding into a model that describes the joint evolution of these factors and finally a component that calculates the impact on banks’ balance sheets (see Summer, 2008). Depending on the distributional assumptions and the modelling framework, the loss distribution can be derived either analytically or by simulating this chain repeatedly. We follow this approach, and obtain our distributions by simulation techniques. At time zero the balance sheet is fixed and all initial coupons are priced based on the observed macroeconomic conditions. At the beginning of $t=1$, we first draw a vector of random macroeconomic shocks and use a Global VAR (in the spirit of e.g. Pesaran et al., 2004) to determine the state of the macroeconomy, including a risk-free yield curve. Using a simple set of regression models, we then obtain PDs conditional on the new macro conditions. At this point the bank can reprice all assets and liabilities in the first repricing bucket, which already allows us to calculate NI. We then simulate (conditionally independent) defaults to derive $L$ and $RNI$ and hence net profits $NP$. At the end of the quarter the bank rebalances its balance sheet in line with the behavioural assumptions presented in Section 3.2. The remaining forecast periods follow the same structure, except that the repricing mechanism becomes increasingly complex as different assets and liabilities are repriced at different points in time as discussed in Section 3.2.

Our initial macroeconomic and balance sheet data are end-2005, and the forecast horizon is one year. We simulate 10,000 macro scenarios. In each of these scenarios, we draw one realisation per quarter of the portfolio loss distribution using Monte Carlo methods.

4.1. The hypothetical bank

Table A1 in Appendix C provides an overview of the balance sheet used for the simulation. It represents the banking book of a simplified average UK bank as exposures in various risk and repricing buckets are derived by averaging the published balance sheets of the top ten UK banks. In order to limit the number of systematic risk factors we have to model, we assume that the bank only has exposures to UK and US assets. We look at seven broad risk classes in both the UK and the US: interbank; mortgage lending to households; unsecured lending to households; government lending; lending to PNFCs (private non financial corporations); lending to OFCs (other financial corporations, i.e. financial corporations excluding banks); “other”. Exposures within an asset class are homogenous with respect to PDs and LGDs. We assume that the bank is fully funded by UK deposits. These consist of interbank, household, government, PNFC, OFC, subordinated debt, and “other”.

Contrary to DSS, we model a portfolio which is not infinitely fine grained. Since no data are available on the size of the exposures, we construct a hypothetical loan size distribution for each asset class. We assume that asset sizes are log-normally distributed with variance one and a mean of £300,000 for household, government, PNFC and OFC, and fine-grained portfolio. This only reduced the tail of the credit risk loss distribution in our model.

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All exposures are assumed to be non-tradeable and held to maturity using book value accounting. In line with accounting standards, assets and liabilities are allocated to five repricing buckets as shown in Table A1. For the actual analysis assets, liabilities and off-balance sheet items in the last three buckets are assumed to be uniformly distributed over quarters within each bucket. For the last bucket we assume that the maximum time to repricing is ten years. The interest rate sensitivity gap is the difference between assets and liabilities in each repricing bucket.

It is important to stress that we are using repricing buckets rather than maturity buckets in order to correctly capture the impact of changes in the macroeconomic environment on the bank’s net interest income. This means that, for example, a flexible mortgage with a 20-year maturity that repays every three-months is allocated to the three-month repricing bucket. As DSS show, the repricing characteristics are the key determinant of interest rate risk in the banking book. The interest rate sensitivity gap relative

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10 We also undertook a sensitivity test to assess the implications of an infinitely fine-grained portfolio. This only reduced the tail of the credit risk loss distribution in the standard fashion. Results are therefore not discussed here but presented in the working paper version (see Alessandri and Drehmann, 2010).
to total assets of our balance sheet is fully in line with the average interest rate sensitivity gap of the top ten UK banks in 2005. Given that in the UK mortgage borrowers predominantly borrow on a flexible rate basis, a high proportion of assets are allocated to the 0–3 months repricing bucket (see Table A1).11

In contrast to DSS we do not look at interest sensitive off-balance sheet items. UK banks on average use these items to narrow the repricing gap between short term borrowing and long term lending. Hence, the interest rate risk estimated in this paper should be more significant than for the actual average UK bank. The repricing structure of the balance sheet is crucial in determining interest rate risk, so we perform a number of sensitivity tests on our baseline assumptions.

4.2. Macro model, PDs and LGDs

To model the macro environment, we implement a two-country version of Pesaran et al.’s (2004) Global VAR model. We treat the UK as a small open economy and the US as a closed economy that is only subject to domestic shocks.12 Variables and data are the same as in Dees et al. (2007). For the UK, these include real output, consumer price inflation, real equity prices, an overnight nominal interest rate, a 20-year synthetic nominal bond interest rate and the real exchange rate against the dollar. For the US, the latter is replaced by oil prices. The model is estimated over a 1979Q1–2005Q4 sample. Our simulations are thus driven by (a sequences of) macro-economic shocks drawn from a multivariate normal distribution based on the estimated historical variance–covariance matrix. Our pricing model requires a full risk-free nominal yield curve. We choose the simplest possible specification, and obtain the curve by a linear interpolation of the overnight and 20-year UK rates.

As mentioned in Section 4.1, we assume that loans within a particular asset class are homogenous with respect to their risk characteristics, i.e. they all have the same PD and LGD. This assumption is dictated by data limitations, as only aggregate default frequencies for corporate and household lending are available in the UK. To estimate the impact of macro factors on PDs we use simple equations in the spirit of Wilson (1997a,b). In particular, each asset’s default frequency is modelled as a function of output growth, return on equity and interest rates. We use plain linear regressions, modelling the log-odd transformation of the default frequency to guarantee that all implied PDs are bounded between zero and one; the resulting regressions have R-squared coefficient ranging from 5% to 30%. We assume that LGDs are fixed. Broadly in line with average industry numbers, we assume an LGD of 40% for interbank loans, 30% for mortgage loans, 100% for credit card loans and 80% for corporate loans.

Both the GVAR and the PD equations were developed as part of a large systemic risk modelling project currently under way at the Bank of England. Alessandri et al. (2009) describe the prototype version of this model, providing more details on the estimation and calibration of these components as well as the underlying data.

We stress that the accuracy of these models is actually not central to our argument: what we need is a plausible, if basic, characterisation of the main sources of co-movement between macroeconomic variables, interest rates and defaults. In principle it is of course possible to incorporate in our framework more sophisticated yield curve, PD or LGD models.

4.3. Pricing of assets and liabilities

We calculate coupons on loans using the risk-neutral pricing model proposed in DSS (see Appendix A). Given the non-linearity of the model, we can only implement the framework by introducing two approximations. These are discussed in detail in Appendix B, where we also show that they do not bias our results. It is well known that there is no simple mapping from actual PDs, which we simulate, into risk-neutral PDs, which we require for pricing (see e.g. Duffie and Singleton, 2003). At this stage it is not possible to find an approach in the literature which could be easily implemented in our already complex model. Hence, we simply introduce a set of fixed risk premia (see Table A2 in Appendix C), undertaking various sensitivity tests to make sure that these assumptions do not drive our results.

In theory, the bank’s liabilities should be priced similarly to assets using the bank’s own PD and LGD. While this seems to be the case for banks’ debt instruments, it is well known that shorter-term customer deposit rates are generally below the risk-free interest rate even when accounting for non-interest costs and fees (e.g. see Corvol and Gropp, 2002). While an economic rationalisation of negative spreads can be found for short maturities, it is not convincing for medium to long maturities. We assume that, as the time to repricing increases, the interest paid by the bank on deposits gradually converges to the risk-free interest rate. Other liabilities pay the risk-free interest rate or in case of subordinate debt, interbank and other liabilities the risk-free interest rate plus a fixed 15 bp spread. All liability spreads are summarized in Table A3 in the Appendix.

5. Results

5.1. Macro factors, PDs and interest rates

Since we use (log)linear models with normally distributed shocks, all macro variables and PDs are roughly normally distributed. Average growth is around 2%, but the GVAR generates several recessionary scenarios where growth turns negative. Interest rates change by 100 basis points or more quite often over the four quarters. On the whole, default probabilities are fairly low and not very volatile (for instance, the annualised UK unsecured personal loan PD has a 90% confidence interval of about 4.3–6.5%). This is partly due to the initial conditions: PDs were indeed very low in 2005 by historical standards. But it also reflects the relatively weak impact of macro factors on default rates in the PD model used for the simulation.13

5.2. The impact on the bank

Fig. 1 and Table 1 provide an overview over various components of the profit and loss distribution. Even though macro variables and PDs are roughly normally distributed, credit risk losses show the characteristic fat tail (Panel A). Credit risk losses range from a min-

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11 The average interest rate sensitivity gap relative to total assets in the UK is stable over time, but given varying economic and institutional conditions there are differences across countries. For example, given a much higher proportion of fixed rate mortgages 50.2% of loans and securities have a remaining time to repricing greater than one year for the average US bank, in comparison to 20.7% for the average UK bank (at the end of 2005). The liability side looks more similar for the average UK and US bank. For the latter 12.5% of liabilities have a remaining time to repricing of more than a year, whereas the proportion in the UK is 8.3% (for US data see FFIEC, 2006).

12 From a UK perspective, this can be interpreted as a GVAR based on a degenerate weighting scheme whereby the ‘rest of the world’ only consists of the US. Given that we only model two countries, we cannot rely on Pesaran et al.’s (2004) asymptotic weak exogeneity result. However, given the relative size of the two countries, our small/big economy assumption holds reasonably and allows us to estimate the model by a standard OLS procedure.

13 For a detailed discussion of outcomes for macro variables and PDs, see Alessandri and Drehmann (2010).
imum of 0.8 bn to a maximum of 16 bn. Interestingly, mean credit risk losses are around 1.37 bn, which fits reasonably closely with the reported average provisions of UK banks of 1.59 bn for 2006 – the year we forecast – even though our balance sheet is highly stylised and losses do not map one-to-one into provisions.

In line with the distribution of simulated interest rates, net interest income (Panel B) is roughly normally distributed and it shows a much smaller variance than the credit risk loss distribution.14 The mean realised net interest income, which also accounts for defaulted coupons, is 4.8 bn. This is lower than the reported average net interest income of 6.32 bn for 2006, possibly because the spreads we add to the risk-neutral coupon rates are not high enough. Clearly, this may also be a result of our assumed balance sheet as our bank is only funded in one currency.

Panel B also shows that the impact of defaulted coupons on realised net interest income (\(RNI\)) is relatively small in absolute terms. As expected, the reduction in net interest income due to defaulted coupon rates (Panel C) is exactly in line with the credit risk loss distribution (Panel A). Overall, the net profit distribution (Panel D) shows a significant negative fat tail, even though net profits are positive in more than 98% of the simulations.

5.3. Economic capital

Table 2 provides an overview of economic capital against different risks at different confidence levels. Given the skew of the credit risk loss distribution, economic capital against credit risk (\(EC_{CR}\)) is non-linearly increasing in the confidence level. This is less pronounced for economic capital against changes in net interest income (\(EC_{NI}\) and \(EC_{RNI}\)) because the underlying net income distributions only show a slight skew. The ratio of \(EC_{RNI}\) to \(EC_{CR}\) therefore decreases from around 30% at the 95% confidence level to 11% at the 99.9% confidence level. These numbers seem broadly in line with banks’ practices. For example, the IFRI-CRO (2007) report suggests that for an average bank the ratio of the capital set against interest rate risk relative to capital set against credit risk is 16%. But given different balance sheet structures, this ratio exhibits a significant variance and can reach 50% or more.

The key question of this paper is whether simple economic capital provides an upper bound. Simple economic capital is the sum of \(EC_{NI}\) and \(EC_{CR}\). It is positive at all confidence levels. However, taking the complex dynamic interactions of credit and interest rate risk into account, the bank makes positive net profits in more than 95% of the scenarios. Therefore, integrated economic capital (\(EC_{NI}\)) at this confidence level is zero. Even at the 99% confidence level, integrated economic capital would be minimal and less than 3% of simple economic capital. Only at the 99.9% percentile economic capital against net profits reaches a substantial amount, but is still only around 50% of simple economic capital.

The difference between simple and integrated economic capital is very large. The bottom of the table shows that this gap is mostly

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14 Throughout the paper we assume that assets and liabilities are priced fairly at the beginning of the simulation. As an additional robustness check we also ran simulations assuming that assets and/or liabilities are 20% over or under-priced. The initial mis-pricing changes only the mean of the net profits distribution but not its shape in line with the results shown in Section 6.1 therefore not discussed further. Results are available on request.
due to the fact that integrated capital covers only unexpected nega-
tive profits. As we explain in Section 3.3, $M_2$ is an alternative mea-
sure that treats profits in the same way as credit risk losses, assuming that capital is set aside against unexpectedly low profits independently of whether these are positive or negative. By this metric, integrated capital is again lower than simple capital but only by an 8% to 20% margin (depending on the confidence level)

In Section 3.3 we argue that $M_3$ is not an economically sensible indicator, so in the reminder of the discussion we focus on $M_{EC}$
and report $M_2$ purely for completeness. In any case, our main result proves to be extremely robust: in all the cases we consider, simple economic capital provides an upper bound independently of
whether we look at $M_{EC}$ or $M_2$.

6. Sensitivity analysis

In this section we test the robustness of our results to alterna-
tive specifications of three key characteristics of the bank: pricing behaviour, repricing maturity mismatch, and funding structure (equity versus deposits).15

6.1. The impact of pricing

To assess the impact of different pricing assumptions, we (i)
drop all spreads on deposits, (ii) drop all exogenous spreads
(including those on deposits), and (iii) drop all exogenous and
endogenous spreads, i.e. we assume that all assets and liabilities
are priced as risk-free instruments. The latter test is roughly equi-
valent to a standard gap analysis, the simplest approach to assess
interest rate risk in the banking book.

The spreads have no impact on the credit loss distribution, so $EC_{CR}$ is exactly the same as in the base case (see Table 3). But endogenous and exogenous spreads boost income significantly:
relative to the baseline, NI falls on average by 30% in the first case,
50% in the second and 59% in the third. In the first two cases we
remove additive, exogenous spreads, so the distributions of
50% in the second and 59% in the third. In the first two cases we
endogenous and exogenous spreads boost income significantly:

Net-profits 3404 3581 815
Note: in millions.

The spreads have no impact on the credit loss distribution, so $EC_{CR}$ is exactly the same as in the base case (see Table 3). But endogenous and exogenous spreads boost income significantly:
relative to the baseline, NI falls on average by 30% in the first case,
50% in the second and 59% in the third. In the first two cases we
remove additive, exogenous spreads, so the distributions of
and RNI only shift downward but maintain the same shape. In
the third case the distribution changes in a more complex way,
but again the dominant feature is the downward shift. As spreads
essentially affect the mean but not the shape of the net interest
income distribution, changes in $EC_{RNI}$ are negligible (at most 3.5% re-
relative to the base case). However, without spreads the bank incurs
net losses more often, so $EC_{NI}$ is higher than in the base case at all
confidence levels. As a consequence, the difference between simple and
integrated economic capital is less pronounced. However, it re-
mains large and positive even under risk-free pricing (case (iii)).

6.2. The impact of the repricing mismatch

To assess the implications of different repricing assumptions, we examine two extreme cases. In the first one (“short L”) we as-
sume that the bank is fully funded by liabilities that are repriced at
every quarter. In the second (“long L”) all liabilities are assumed to have a time to repricing of more than one year. Given our one year horizon, this means that they are never repriced and generate fixed
net interest payments. Both experiments imply a much higher vol-
atility of NI. Interestingly, though, volatility is three times higher in
the “long L” case than in the “short L” case. The reason is simple: income volatility depends on the interest rate sensitivity gap,
and in absolute terms this is actually highest in the “long L” case.16
As Table 4 shows, higher income volatility translates into much lar-
ger $EC_{CR}$ estimates at all confidence levels. $EC_{gap}$ is also consistently
higher than in the baseline, whereas $M_{EC}$ does not give a clear mes-
 sage. Nonetheless, once again, simple economic capital exceeds inte-
grated economic capital in all cases.

6.3. The impact of equity

Our last set of tests concerns the bank’s equity. In our baseline
calibration, equity is approximately 4% of total assets. Since divi-
dends are only paid from net profits after one year, higher capital
levels affect the bank’s net interest income by lowering total inter-
est payments on liabilities. We replicated our calculations for ini-
tial equity levels of 0%, 4% and 8% of total assets, setting all
exogenous asset and liability spreads to zero to better isolate the
role of equity. Credit losses are not affected by the equity level,
whereas the impact on the NI distribution is substantial: reducing
credit loss from 8% to 4% decreases the mean NI by 22% and increases
its standard deviation by more than 50%. Setting equity to zero de-
creases the mean NI by nearly another 40% and increases the stan-
dard deviation by an additional 26%.

15 We only report the tables on capital calculations here. More detailed results on
each of these sensitivity tests are presented in the working paper version (see
Alessandri and Drehmann, 2010).

16 The interest rate sensitivity gaps for the 1–3 months bucket are −23% for “short
L”, −10% for the base case and +52% for “long L”. Note that in the “long L” case the gap
is positive, i.e. contrary to standard banks this bank borrows long and lends short.

Table 1
Losses, income and profits.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
<th>.1%</th>
<th>1%</th>
<th>5%</th>
<th>95%</th>
<th>99%</th>
<th>99.9%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit risk losses</td>
<td>1378</td>
<td>1146</td>
<td>765</td>
<td>835</td>
<td>15,788</td>
<td>933</td>
<td>990</td>
<td>1033</td>
<td>2726</td>
<td>4790</td>
<td>8871</td>
</tr>
<tr>
<td>Net interest income (NI)</td>
<td>4810</td>
<td>4810</td>
<td>259</td>
<td>3793</td>
<td>5680</td>
<td>4014</td>
<td>4199</td>
<td>4386</td>
<td>5233</td>
<td>5395</td>
<td>5535</td>
</tr>
<tr>
<td>Net interest including losses due to defaulted coupons (RNI)</td>
<td>4782</td>
<td>4781</td>
<td>260</td>
<td>3764</td>
<td>5647</td>
<td>3973</td>
<td>4170</td>
<td>4353</td>
<td>5206</td>
<td>5371</td>
<td>5514</td>
</tr>
<tr>
<td>Net-profits</td>
<td>3404</td>
<td>3581</td>
<td>815</td>
<td>-10,991</td>
<td>4570</td>
<td>-4183</td>
<td>-112</td>
<td>2031</td>
<td>4061</td>
<td>4251</td>
<td>4434</td>
</tr>
</tbody>
</table>

Note: in millions.

Table 2
Economic capital.

<table>
<thead>
<tr>
<th></th>
<th>Confidence level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>95%</td>
</tr>
<tr>
<td>$EC_{CR}$</td>
<td>1348</td>
</tr>
<tr>
<td>$EC_{NI}$</td>
<td>424</td>
</tr>
<tr>
<td>$EC_{RNI}$</td>
<td>429</td>
</tr>
<tr>
<td>$EC_{CR} + EC_{RNI}$</td>
<td>1777</td>
</tr>
<tr>
<td>$E_{NP}$</td>
<td>0</td>
</tr>
<tr>
<td>$M_2$ (%)</td>
<td>100.00</td>
</tr>
<tr>
<td>$E_{NP} / VaR_{NP}$</td>
<td>1372</td>
</tr>
<tr>
<td>$M_3$ (%)</td>
<td>22.76</td>
</tr>
</tbody>
</table>
We find that the difference between the two risk types may be such that the overall level of capital is higher than the sum of capital derived for risks independently. Risk managers and regulators should work on the presumption that there may be no general answers to this type of questions. As a consequence, capital exceeds integrated capital under a broad range of circumstances, providing an upper bound relative to the bank’s overall risk.

A range of factors contribute to generating this result. A relatively large portion of credit risk is idiosyncratic, and thus independent of the macroeconomic environment, and the correlation between systematic credit risk factors and interest rates is itself not perfect. Furthermore, assets in the bank's portfolio are repriced relatively frequently, and hence increases in credit risk can be partly passed on to borrowers. Our analysis also rests on a number of assumptions: for instance we do not account for prepayment risk (which is negligible in the UK but quite substantial in the US), hedging, or subordinated debt. Given the magnitude and robustness of our results, though, our conjecture is that extending the model in these directions would not change our main conclusion for a similar portfolio.

More importantly, though, we emphasise that, since we focus on traditional banking book risks, relating our insights to the recent crisis is not trivial. Securitisation, derivatives and liquidity management – which were at the core of the turmoil – remain outside the scope of this paper. Furthermore, changes in the economic value of the portfolio are not taken into account as all exposures are assumed to be non-tradable and therefore valued using book value accounting. It is difficult to speculate on whether “integrated capital” would remain lower than “simple economic capital” in a context where these restrictions are relaxed. In fact, the findings in Breuer et al. (2010) and Kupiec (2007) suggest that there may be no general answers to this type of questions. As a consequence, risk managers and regulators should work on the presumption that interactions between risk types may be such that the overall level of capital is higher than the sum of capital derived for risks independently. Our paper shows that this is unlikely for credit and interest rate risk in the banking book, but also that additive rules are in this case potentially very inefficient. From a risk manage-

### Table 3
Economic capital under different pricing assumptions.

<table>
<thead>
<tr>
<th>No negative spreads on liabilities</th>
<th>No additive spreads</th>
<th>Risk free pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence level</td>
<td>Confidence level</td>
<td>Confidence level</td>
</tr>
<tr>
<td>95%</td>
<td>99%</td>
<td>99.9%</td>
</tr>
<tr>
<td>$EC_{nr}$</td>
<td>1348</td>
<td>3412</td>
</tr>
<tr>
<td>$EC_{av}$</td>
<td>415</td>
<td>593</td>
</tr>
<tr>
<td>$EC_{nr} + EC_{av}$</td>
<td>1763</td>
<td>4005</td>
</tr>
<tr>
<td>$E_{CR}$</td>
<td>0</td>
<td>1621</td>
</tr>
<tr>
<td>$M_{EC}$ (%)</td>
<td>100.00</td>
<td>59.52</td>
</tr>
<tr>
<td>$E_{NP}-VaR_{EC}$</td>
<td>1376</td>
<td>3518</td>
</tr>
</tbody>
</table>

See note to Table 2.

### Table 4
Economic capital under alternative funding assumptions.

<table>
<thead>
<tr>
<th>All short</th>
<th>All long</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence level</td>
<td>Confidence level</td>
</tr>
<tr>
<td>95%</td>
<td>99%</td>
</tr>
<tr>
<td>$EC_{nr}$</td>
<td>1348</td>
</tr>
<tr>
<td>$EC_{av}$</td>
<td>978</td>
</tr>
<tr>
<td>$EC_{nr} + EC_{av}$</td>
<td>2326</td>
</tr>
<tr>
<td>$E_{CR}$</td>
<td>0</td>
</tr>
<tr>
<td>$M_{EC}$ (%)</td>
<td>100.00</td>
</tr>
<tr>
<td>$E_{NP}-VaR_{EC}$</td>
<td>1525</td>
</tr>
<tr>
<td>$M_{2}(%)$</td>
<td>34.41</td>
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</tbody>
</table>

See note to Table 2. All exogenous spreads are set as in the baseline simulation.

### Table 5
Economic capital for initial equity levels of 0%, 4% and 8%

<table>
<thead>
<tr>
<th>0% Equity</th>
<th>4% Equity</th>
<th>8% Equity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence level</td>
<td>Confidence level</td>
<td>Confidence level</td>
</tr>
<tr>
<td>95%</td>
<td>99%</td>
<td>99.9%</td>
</tr>
<tr>
<td>$EC_{nr}$</td>
<td>1348</td>
<td>3412</td>
</tr>
<tr>
<td>$EC_{av}$</td>
<td>576</td>
<td>820</td>
</tr>
<tr>
<td>$EC_{nr} + EC_{av}$</td>
<td>1924</td>
<td>4232</td>
</tr>
<tr>
<td>$E_{CR}$</td>
<td>1092</td>
<td>3203</td>
</tr>
<tr>
<td>$M_{EC}$ (%)</td>
<td>43.25</td>
<td>23.55</td>
</tr>
<tr>
<td>$E_{NP}-VaR_{EC}$</td>
<td>1395</td>
<td>3506</td>
</tr>
<tr>
<td>$M_{2}(%)$</td>
<td>27.48</td>
<td>17.15</td>
</tr>
</tbody>
</table>

See note to Table 3. All exogenous spreads are set to zero.
In a broader perspective, this should provide another strong incentive to move towards an integrated analysis of risks.

Acknowledgments

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Appendix A. Endogenous coupon rates

This annex is based on Drehmann et al. (2010). The economic value $EVA^t$ of a generic asset $i$ with time to repricing of $T$ (which is also for simplicity equal to its maturity) is simply the risk-adjusted discounted value of future coupon payments $C_j(X_t)$ and the principal $A_j$.

$$EVA^t_i(X_t) = \sum_{k=1}^{T} D_{t+k}^i(X_t) C_j(X_t) A_j^i + D_{t+1}^i(X_t) A_j$$  \hspace{1cm} (A1)
Credit risk loss distribution (L)
Credit risk loss distribution including defaulted coupons (L*)

For simplicity we assume that all assets are equivalent to bullet bonds – i.e. repay the principal only at maturity and pay a constant coupon $C_i$ that is determined at time $t=s$ based on the observed and expected macroeconomic variables $X_t$. For example, such an asset could be a fixed-interest rate bond with no embedded options or a simple bank loan. The discount factor conditional on current conditions is given by:

$$D_{i,t}^{l}(X_t) = E \left( \prod_{k=1}^{t} \frac{1}{1+R_{t+l-1-t+l}^{i}(X_t)} \right)$$ \hfill (A2)

where $R$ is the risk-adjusted interest rate. In continuous time, $R$ equals the risk-free rate plus a credit risk premium equal to $PDiLGD$. However, as our application is set up in discrete time, we follow Duffie and Singleton (2003):

$$R_{t+l-1-t+l}^{i}(X_t) = \frac{\left( r_{t+l-1-t+l}^{i}(X_t) + PD_{t+l-1-t+l}^{i}(X_t) \times LGDi \right)}{1 - PD_{t+l-1-t+l}^{i}(X_t) \times LGDi}$$ \hfill (A3)

where $r_{t+l-1-t+l}^{i}$ is the forward risk-free interest rate between $t+l-1$ and $t+l$ known at time $t$. $LGD$ is the expected loss given default for borrower $i$ which, for simplicity, we assume here to be constant. $PD_{t+l-1-t+l}^{i}$ is the risk-neutral probability of default of borrower $i$ between $t+l-1$ and $t+l$ conditional on surviving until $t+l-1$. PDs and yields depend on the same set of systematic risk factors $X_t$. We do not observe empirical coupon rates and need to reprice assets and liabilities according to their contractual repricing characteristics. To do so we assume that at the time of issuance the economic value equals the face value of the asset. This implies that $EV_{t+1}(X_0) = A'$ in Eq. (A1). Solving for $C_{i}$ we obtain:

$$C_{i}(X_0) = \frac{1 - D_{i}^{l}(X_0)}{\sum_{k=1}^{t} D_{k}^{l}(X_0)}$$ \hfill (A4)

**Appendix B. Empirical implementation of the pricing framework**

In order to implement our framework, we rely on two approximations. The first one consists of assuming that banks use a random walk model to form expectations on future PDs, i.e. they assume that $E_i(PDi_{t+1}) = PD_i$. Using model-consistent expectations is possible but computationally very cumbersome given the high dimensionality of the model.\(^\text{17}\) In order to assess the implications of this approximation, we replicated the baseline case using model-consistent expectations as a sensitivity test.\(^\text{18}\) This indicates that wrongly formed expectations slightly bias income levels downwards.
and decrease the variance of $\text{RNI}$, which was to be expected as model-consistent expectations are less volatile. Most importantly, the error margins introduced by this approximation for $M_{EC}$ are small and below 2% at all confidence levels.

Second, when calculating the discount factors $D_{t,k}$, we approximate Eq. (A2) as follows

$$D_{t,k} = \left( \prod_{l=1}^{k} \left( \frac{1}{1 + R_{t+1,l+1}} \right) \right) \approx \prod_{l=1}^{k} \left( \frac{1}{1 + R_{t+1,l+1}} \right)$$

$$= \left( \prod_{l=1}^{k} \left( \frac{1}{1 + \text{PD}_{t+1,l+1}} \right) \right) \text{LGD}^l$$

(B1)

The last equality holds as the forward yield curve is known at the time of pricing and LGDs are fixed. By looking at the product of expectations rather than the expectation of the product, though, we ignore any conditional cross-correlations between discount factors at different points in time. It is hard to quantify the bias this introduces as the simulation becomes too complex to calculate coupon rates correctly. However, we would argue that the bias does not affect our results in a significant fashion. As pointed out above, at the time of pricing the forward yield curve is known and LGDs are fixed. Therefore, the conditional correlation is driven by the conditional correlation between PDs. All PDs are by construction conditionally homoscedastic – a property they inherit from the GVAR. Hence, their conditional auto-correlations are constant over time. Furthermore, the realised unconditional auto-correlations are small and positive, and decline rapidly to zero for lag lengths greater than one. This would suggest that the bias is not substantial and that the coupons we calculate are too low on average. Given the robustness tests in Section 6.1, this means that $\text{ECNP}$ in our base case is likely to be too high in comparison to the approximation would not be made.

Appendix C. Additional tables

See Tables A1–A3.

Appendix D. Additional figures

See Figs. A1 and A2.

References


Wilson, T.C., 1997a. Portfolio credit risk (I). Risk 10 (September), 111–117.

Wilson, T.C., 1997b. Portfolio credit risk (II). Risk 10 (October), 56–61.