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Proactive biometric-enabled forensic imprinting

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A Capital Adequacy Buffer Model

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We develop a new capital adequacy buffer model (CABM) which is sensitive to dynamic economic circumstances. The model, which measures additional bank capital required to compensate for fluctuating credit risk, is a novel combination of the Merton structural model which measures distance to default and the timeless capital asset pricing model (CAPM) which measures additional returns to compensate for additional share price risk. We apply the model to a portfolio of mid-cap loan assets over a ten year period which includes pre-GFC, GFC and post GFC. An analysis of actual defaults over this period shows the model to be far more accurate in determining the capital adequacy levels needed to counter credit risk than an unresponsive ratings model such as the Basel standardized approach.

\textit{Keywords:} Credit risk; Capital buffer; Distance to default; Capital adequacy buffer model.

\textit{JEL Classification:} G21, G28

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I. Introduction

Extreme credit risk had a devastating impact on global economic stability during the Global Financial Crisis (GFC). The global banking sector was beset by capital shortages, and large numbers of bank failures. The Basel capital adequacy framework could not cope. Although Basel III subsequently introduced stricter requirements, the standardized model which is used by the majority of US banks (Federal Reserve Bank, 2012) is still based on fairly static credit ratings, which do not change with dynamic economic circumstances. In addition, Basel only provides minimum requirements and banks and regulators themselves need to ensure that their capital buffers can withstand extreme economic circumstances. Wide calls have been made for capital models to be improved on aspects such as less complexity, greater standardization, better alignment to dynamic economic conditions, and less reliance on static credit ratings (see Bichsel and Blum (2012), Kretzschmar, McNeil, and Kirchner (2010). We propose a novel Capital Adequacy Buffer Model (CABM), which meets all these needs, combining simplicity with high market responsiveness. It is based on a combination of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and the Merton (1974) Distance to Default (DD) Model. CAPM’s beauty is its simplicity and effectiveness in pricing risk, and its wide global acceptance. The Merton model, modified by Moody’s KMV, is also widely accepted, with Moody's Analytics (2015) reporting use by more than 2000 firms in over 80 countries including most of the world’s 100 largest financial institutions. The beauty of the Merton model is its rapid response to market conditions, whereby market asset values can be measured even daily if required. CABM combines the benefits of both these models to provide a highly responsive model which introduces a credit beta $\beta$ to estimate capital buffers required for extreme credit risk. Betas have previously been explored for credit risk (Allen, Powell, and Singh, 2015) but this has not included the formulation of a capital adequacy buffer model. We compare our CABM outcomes to actual impaired assets and defaults and find it to be highly accurate and very responsive to changing conditions.

II. Data

To demonstrate the model, we use a portfolio of loan assets comprising the S&P400 mid-cap index, which provide a better mix of higher and lower credit ratings than a high-cap or small cap-index. We use only entities with Moody’s credit ratings (so we can compare our outcomes to Basel as well as to actual defaults for each rating). This yields 177 entities across
18 industries. Our period spans 10 years (2003 - 2012), encompassing a range of economic circumstances including pre-GFC, GFC and post-GFC years. We use the year end Moody’s rating for each entity and year. The assets, liabilities and daily equity information required to calculate DD are obtained for each entity from Datastream. To ascertain the accuracy of our model, we compare outcomes to Moody’s actual default data and to corporate delinquent loan percentages obtained from the U.S. Federal Reserve Bank (2013).

III. Our Capital Asset Buffer Model

In a stock market context beta ($\beta$) measures the systematic risk of an individual security with CAPM predicting what an asset or portfolio’s expected return should be relative to its risk and the market return. Within CAPM is the Capital Market line (CML), where additional volatility ($\sigma$) above a benchmark $\sigma$ or market $\sigma$, needs to be compensated for by additional return above the risk free rate ($R_f$). This is shown in Fig. 1 For CML, $E(R_i)$ is the expected asset return and $E(R_m)$ is the market return.

$$E(R_i)=R_f+\beta_i(E(R_m)-R_f) \quad (1)$$

CABM follows a similar thought process to CAPM, but instead of extra returns compensating for share price volatility above a risk-free rate, we measure additional capital required to compensate for additional volatility in market asset values (as measured by the Merton model) above a specified benchmark. As the Merton model is well documented, we will not explain it here, suffice it to say that we follow the Merton model procedures for measuring asset volatility ($\sigma_V$) as outlined in Bharath and Shumway (2008).
\( \beta \) is measured as the market asset volatility of asset \( i \) (\( \sigma_{V_i} \)) divided by benchmark volatility (\( \sigma_b \)), which is the level of market asset volatility associated with a benchmark capital (\( K_b \)). \( K_b \) is the prescribed minimum level of capital for any asset in a portfolio.

\[
\beta = \frac{\sigma_{V_i}}{\sigma_b}
\]  
(2)

CAPM’s CML is re-defined as the Capital Buffer Line (CBL) as shown in Fig. 1, which shows additional capital required for risky loan assets. Capital required (\( K_i \)) for asset \( i \):

\[
K_i = \left( \frac{\sigma_{V_i}}{\sigma_b} K_b \right) = \beta K_b
\]  
(3)

Additional capital required for asset \( i \) (\( K_{a_i} \)) to compensate for risk above the benchmark rate:

\[
K_{a_i} = \left( \frac{\sigma_{V_i}}{\sigma_b} K_b \right) - K_b
\]  
(4)

Under the Merton model, default occurs when asset values (\( V \)) fall below liabilities (\( F \)), which occurrence is influenced by volatility in asset values. DD in its simplest form (Crosbie and Bohn, 2003):

\[
DD = \frac{(V - F)}{V(\sigma_v)}
\]  
(6)

We simplify this even further:

\[
DD = \frac{K}{\sigma_v}
\]  
(7)

Where \( K \) is the capital held as a percentage of the relevant asset or portfolio. Our benchmark capital (\( K_b \)) is the minimum capital which a bank is required to maintain, and any increase in the \( \sigma_v \) denominator requires a proportionately equal increase in the capital numerator to restore the DD.

IV. Applications of CABM

Under Basel III, a bank must hold 8% capital, multiplied by risk weighted assets (RWA). A bank or regulator can opt out of the external ratings approach and hold 100% RWA against all corporate assets, which the US has chosen to do. To compare the results of our model to Basel, we will assume here that a ratings based approach applies, but we also comment on how this would change if opting out. Moody’s state that their ratings show relative risk, rather than absolute risk, but from a Basel perspective this has important ramifications,
because an unchanged rating in turbulent times means unchanged capital requirements. The right hand side of Table 1 shows the RWA, the $\beta$ applying to the RWA ($\beta_{RWA}$, which we explain in the following paragraph), and the required capital ($K$) under Basel. When Basel III is fully phased in, banks will also be required to hold a 2.5% capital conservation buffer, which will improve the overall capital situation of a bank. Nonetheless, this falls well short of our CABM outcomes.

The LHS of Table 1 shows CABM outcomes. Just as CAPM $\beta$ benchmarks a stock to the average market, CABM benchmarks a particular year to an average year (a bank or regulator could set a benchmark of their choice). This capital requirement fluctuates with changes in $\sigma_V$, where $\beta_V$ represents $\sigma_V / \sigma_b$ (and $\beta_{RWA}$ represents changes in RWA). Capital may not fall below $K_b$.

The average annual portfolio RWA (using Basel III weightings, based on each of the assets’ credit ratings in the portfolio, was 94%. Multiplied by the 8% Basel capital requirement, this provides a risk weighted capital of 7.5%, which we set as $K_b$.

Table 1 shows how the Basel standardized model has little fluctuation in capital requirements ($K$) over the period (6.56% to 8.21% with a maximum $\beta$ of 1.09). Indeed, Table 1 shows that under Basel, $K$ was at one of its lowest points in 2008, the height of the GFC, because ratings had not yet responded to market conditions. If a bank opted out of external ratings, there would be no fluctuation, as capital stays at 8% across the period, with a $\beta$ of 1. CABM has much greater fluctuation, with $K$ more than doubling over the period to a $\beta$ of 2.2. We used daily asset values to obtain $\sigma_V$ and the standard errors (SE) are low. This large spread in volatility is indicated in Fig. 2. Our benchmark DD, based on the 10 year average, was calculated to be 7.41 standard deviations away from default, reducing by 2.2 times in 2008 according to the $\beta$, requiring capital to be increase by the same proportion to 16.53% to restore DD. The required capital ($K$) for each level of $\sigma_V$ can be read off the CBL. The importance of countercyclical buffers is emphasized by many authors (see for example Drehmann and Gambacorta, 2012; Ibáñez-Hernández, Peña-Cerezo, and Araujo, 2015).

Under our model, banks should hold a consistent countercyclical capital buffer which covers all the economic periods, but reassess it as circumstances change. The Merton model which underpins CABM, not only allows the calculation of this buffer, but as it is based on daily market asset values, it also allows volatility (and hence capital) to be reassessed frequently, even daily, thus providing an early warning signal if circumstances rapidly deteriorate.
To be confident in our model, we compare the indicated risk and capital levels to actual default levels experienced for rated entities. We obtain annual default figures by rating from Moody’s global default database for each of our 10 years, and match these to the rating of every entity in our portfolio. We calculate a weighted average portfolio default $\beta$, which in line with CABM is based on the maximum annual portfolio default figure divided by the average default figures for ten years. This yields a default $\beta$ based on Moody’s figures of 2.32, just slightly more than CABM’s $\beta$ of 2.20. Given the highly detailed nature of this comparison with actual Moody’s defaults (rating by rating, year by year), this can be considered to be a very extensive and accurate comparison. Additionally, we compare our results to corporate delinquent loan figures from the U.S. Federal Reserve Bank (2013). This is less accurate than our comparison to Moody’s default figures as the delinquent loan figures are not split by rating. Nonetheless, it gives an idea of overall corporate default volatility across the market. We calculate $\beta$ for these delinquencies at 1.92, slightly under our 2.20 CABM Beta, but again, much more accurate than the 1.09 Basel maximum $\beta_{RWA}$ for this portfolio.

V. Conclusions and policy prescriptions.

We have developed an innovative CABM model which measures fluctuating asset values and the capital required to compensate for risk above a benchmark. The advantages of the model are its simplicity and incorporation of the well-established techniques of CAPM and the Merton DD model. Comparison to actual defaults show the model to be far more accurate in determining the capital adequacy levels than a ratings based model. CABM could be used at three different policy levels to facilitate these buffer calculations. At the global level, it could be used to modify the Basel standardized model policy, by providing $\beta$’s attached to each credit rating. At the member regulator level, $\beta$’s could be reviewed regularly as part of the regulator policy for reviewing capital adequacy according to the particular economic circumstances of the member country. At a bank policy level, banks could use CABM as part of their internal capital adequacy modeling policy. Basel could set the time intervals at which $\beta$’s are required to be reviewed by regulators, and regulators could set them for banks. CABM is extremely flexible in the use of time periods, given that asset values can be measured at any chosen time interval, such as daily, monthly, quarterly, annually, or even longer to cover different cycles.
References


Fig. 1. Comparing CABM’s CBL to CAPM’s CML

Fig. 2. CBL for mid-cap portfolio
Table 1. CABM results for mid-cap portfolio

<table>
<thead>
<tr>
<th>Year</th>
<th>CABM σv</th>
<th>CABM SE</th>
<th>CABM βv</th>
<th>CABM K</th>
<th>Basel standardised capital RWA</th>
<th>Basel standardised capital βRWA</th>
<th>Basel standardised capital K</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>16.02%</td>
<td>1.01%</td>
<td>0.80</td>
<td>7.50%</td>
<td>95.00%</td>
<td>1.01</td>
<td>7.60%</td>
</tr>
<tr>
<td>2004</td>
<td>14.58%</td>
<td>0.92%</td>
<td>0.73</td>
<td>7.50%</td>
<td>91.58%</td>
<td>0.98</td>
<td>7.33%</td>
</tr>
<tr>
<td>2005</td>
<td>13.62%</td>
<td>0.86%</td>
<td>0.68</td>
<td>7.50%</td>
<td>91.01%</td>
<td>0.97</td>
<td>7.28%</td>
</tr>
<tr>
<td>2006</td>
<td>14.17%</td>
<td>0.90%</td>
<td>0.71</td>
<td>7.50%</td>
<td>91.59%</td>
<td>0.98</td>
<td>7.33%</td>
</tr>
<tr>
<td>2007</td>
<td>20.63%</td>
<td>1.30%</td>
<td>1.04</td>
<td>7.77%</td>
<td>81.98%</td>
<td>0.87</td>
<td>6.56%</td>
</tr>
<tr>
<td>2008</td>
<td>43.93%</td>
<td>2.78%</td>
<td>2.20</td>
<td>16.53%</td>
<td>88.13%</td>
<td>0.94</td>
<td>7.05%</td>
</tr>
<tr>
<td>2009</td>
<td>23.56%</td>
<td>1.49%</td>
<td>1.18</td>
<td>8.87%</td>
<td>95.48%</td>
<td>1.02</td>
<td>7.64%</td>
</tr>
<tr>
<td>2010</td>
<td>16.19%</td>
<td>1.02%</td>
<td>0.81</td>
<td>7.50%</td>
<td>100.34%</td>
<td>1.07</td>
<td>8.03%</td>
</tr>
<tr>
<td>2011</td>
<td>21.20%</td>
<td>1.34%</td>
<td>1.06</td>
<td>7.98%</td>
<td>102.66%</td>
<td>1.09</td>
<td>8.21%</td>
</tr>
<tr>
<td>2012</td>
<td>15.38%</td>
<td>0.97%</td>
<td>0.77</td>
<td>7.50%</td>
<td>101.45%</td>
<td>1.08</td>
<td>8.12%</td>
</tr>
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