Assessing the Basel II Internal Ratings-Based Approach: Empirical Evidence from Australia

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Abstract

The Basel II internal ratings-based (IRB) approach to capital adequacy for credit risk implements an asymptotic single risk factor (ASRF) model. Measurements from the ASRF model of the prevailing state of Australia’s economy and the level of capitalisation of its banking sector find general agreement with macroeconomic indicators, financial statistics and external credit ratings. However, given the range of economic conditions, from mild contraction to moderate expansion, experienced in Australia since the implementation of Basel II, we cannot attest to the validity of the model specification of the IRB approach for its intended purpose of solvency assessment. With the implementation of Basel II preceding the time when the effect of the financial crisis of 2007–09 was most acutely felt, our empirical findings offer a fundamental assessment of the impact of the crisis on the Australian banking sector. Access to internal bank data collected by the prudential regulator distinguishes our research from other empirical studies on the recent crisis.

Keywords: internal ratings-based (IRB) approach, asymptotic single risk factor (ASRF) model, credit value-at-risk (VaR), distance to default, reverse stress testing, financial crisis.

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1. Introduction

Under the Basel II Accord, authorised deposit-taking institutions (ADIs) determine regulatory capital for credit risk using either the standardised approach or, subject to approval, the internal ratings-based (IRB) approach. The latter is more expensive to administer, but usually produces lower regulatory capital requirements than the former. As a consequence, ADIs using the IRB approach may deploy their capital in pursuit of more (profitable) lending opportunities. This paper examines the model specification of the IRB approach, the so-called asymptotic single risk factor (ASRF) model. We render an assessment of the ASRF model by taking readings of the Australian banking sector since the implementation of Basel II and comparing them with signals from macroeconomic indicators, financial statistics and external credit ratings. The relatively short quarterly time series available leads to an intuitive assessment of the ASRF model rather than any formal testing of its efficacy. Any evaluation of the model specification of the IRB approach requires access to internal bank data, which are input to the model. Support for this research by the Australian Prudential Regulation Authority (APRA) includes access to these data.

Upon implementation of Basel II in the first quarter of 2008, APRA had granted the four largest Australian banks, designated “major” banks, approval to use the IRB approach to capital adequacy for credit risk. In order to take measurements from the ASRF model of the Australian banking sector, we aggregate data reported to APRA by the major banks on a quarterly basis since the implementation of Basel II. We contend that these data are representative of the Australian banking sector on the basis of the market dominance of the major banks, and the concentration of their regulatory capital held against unexpected credit losses projected by the IRB approach. The ASRF model calculates the expectation of credit losses conditional on a realisation of the single systematic risk factor, which is interpreted as describing the state of the economy, in order to assess regulatory capital charges. Substituting credit losses incurred into the ASRF model, we solve for realisations of the single systematic risk factor describing the prevailing state of the Australian economy. Then, substituting provisions and capital held against credit losses into the ASRF model, and translating realisations of the single systematic risk factor into distances to default, we measure the level of capitalisation of the Australian banking sector. We find that time series of the prevailing state of the economy and real GDP growth are quite highly correlated, while the banking sector maintained a level of capitalisation reflective of a strong credit rating. Our empirical findings comport with signals from macroeconomic indicators, financial statistics and external credit ratings.

The range of economic conditions, from mild contraction to moderate expansion, experienced in Australia since the first quarter of 2008 translate into observations away from the tail of the distribution of the single systematic risk factor, and hence the portfolio loss distribution. Accordingly, we argue that our findings support a favourable assessment of the ASRF model for the purposes of capital allocation, performance attribution and risk monitoring — management functions that need only be accurate in the measurement of relative risk under “normal” economic conditions. The IRB approach, however, serves the sole purpose of solvency assessment, which requires precision in the measurement of absolute risk levels under stressed economic conditions, or tail events (Basel Committee on Banking Supervision et al., 2010). Therefore, we cannot attest to the suitability of the ASRF model for regulatory capital modelling. Evaluating the model specification of the IRB approach for its intended purpose of solvency assessment would involve taking readings of banking jurisdictions that have experienced a full-blown economic or financial crisis since the implementation of Basel II. It would supplement the findings of this study.

In assessing the model specification of the IRB approach, this paper presents a methodology for regulators to monitor the prevailing state of the economy as described by the single systematic
risk factor, and the capacity of supervised banks to absorb credit losses as measured by distance to default. Measurements from the ASRF model signalling an overheating economy and procyclical movements in capital bases, corroborated by macroeconomic performance indicators including rapidly accelerating credit growth, would prompt supervisors to lean against the prevailing winds by instructing banks to build up countercyclical capital buffers introduced under Basel III.

The financial crisis of 2007–09, also known as the global financial crisis, precipitated the worst global recession since the Great Depression of the 1930s. Its effects, however, were not felt evenly across the globe, and the Australian economy was largely spared. With the implementation of Basel II preceding the time when the effect of the crisis was most acutely felt, our empirical analysis reveals that the crisis imparted a mild stress on the Australian banking sector. We are not the first to attempt to measure the effects of the recent crisis, but we believe that we are the first to do so using regulatory data. In evaluating the model specification of the IRB approach we produce a fundamental assessment of the impact of the crisis on the Australian banking sector using internal bank data collected by APRA. Other studies on the financial crisis rely on market data, macroeconomic indicators or published financial statistics. In arguing the resilience of the Australian economy to the crisis, McDonald and Morling (2011), and Brown and Davis (2010) describe its performance primarily in terms of macroeconomic indicators and financial statistics. Our measurements from the ASRF model of the Australian banking sector corroborate their observations. Allen and Powell (2012), on the other hand, rely on market data and reach a markedly different conclusion about the condition of the Australian banking sector during the recent crisis. We submit that their results are biased by plummeting market prices and spiking volatility reflecting the overreaction of market participants gripped by fear at the depths of the crisis.

We begin in Section 2 by outlining the model specification of the IRB approach. In Section 3 we describe the Basel II capital adequacy reports that supply data for our empirical analysis. Section 4 contextualises the Australian economy over the past decade by comparing its performance with those of the United States and United Kingdom on macroeconomic indicators and financial statistics. Explanations proffered for the recent performance of the Australian economy and its resilience to the financial crisis are discussed in some detail. Measurements from the ASRF model of the Australian banking sector since the implementation of Basel II are presented in Section 5. Realisations of the single systematic risk factor describing the prevailing state of the economy measure the impact of the crisis on the Australian banking sector, while estimates of distance to default reflect its capacity to absorb credit losses. In a variation on the evaluation of distance to default, reverse stress testing explores stress events that would trigger material supervisory intervention. We conclude by outlining the direction for future related research.

2. Model Specification of the Internal Ratings-Based Approach

The Basel II IRB approach implements an asset value factor model of credit risk. Asset value models posit that default or survival of a firm depends on the value of its assets at a given risk measurement horizon. If the value of its assets is below a critical threshold, its default point, the firm defaults, otherwise it survives. Asset value models have their roots in Merton’s seminal paper (1974). Factor models are a well established, computationally efficient technique for explaining dependence between variables (Bluhm et al., 2010).

The model specification of the IRB approach assesses capital charges sufficient to absorb credit losses, and thus protect against insolvency, with a high level of confidence. It applies value-at-risk (VaR), one of the most widely used measures in risk management, to assign a single numerical value to a random portfolio credit loss. Let random variable $\mathcal{L}_n$ be the (dollar) loss on a credit portfolio comprising $n$ obligors over a given risk measurement horizon. Adopting the convention that a loss is a positive number, we define *credit VaR* at the confidence level $\alpha \in (0,1)$ over a
given risk measurement horizon as the largest portfolio credit loss $l$ such that the probability of a loss $\mathcal{L}_n$ exceeding $l$ is at most $(1-\alpha)$:

$$\text{VaR}_\alpha(\mathcal{L}_n) = \inf\{l \in \mathbb{R} : \mathbb{P}(\mathcal{L}_n > l) \leq 1 - \alpha\}. \quad (2.1)$$

In probabilistic terms, $\text{VaR}_\alpha(\mathcal{L}_n)$ is simply the $\alpha$ quantile of the portfolio loss distribution, typically a high quantile that is rarely exceeded. Although computationally expensive, Monte Carlo simulation is routinely employed to generate the empirical loss distribution and determine VaR of a credit portfolio. An analytical model of the portfolio loss distribution, on the other hand, facilitates the fast calculation of credit VaR.

The IRB approach rests on a proposition due to Gordy (2003), which leads to an analytical approximation to credit VaR, the so-called asymptotic single risk factor (ASRF) model. It assumes that:

1. Portfolios are infinitely fine-grained so that idiosyncratic risk is fully diversified away.
2. A single systematic risk factor explains dependence across obligors.

As a practical matter, credit portfolios of large banks are typically near the asymptotic granularity of Condition (1). Furthermore, Gordy and Lütkebohmert (2003) propose a granularity adjustment for quantifying the contribution of name concentrations to portfolio risk, and hence assessing a capital charge for undiversified idiosyncratic risk. So, moderate departures from asymptotic granularity need not pose an impediment to assessing ratings-based capital charges.

Assume that latent random variables modelling the variability in obligors’ asset values are standard Gaussian and conditionally independent given systematic risk factor $Y$. Assume that $\delta_i \in \mathbb{R}$, and $\eta_i \in [0, 1]$ the EAD and LGD, respectively, assigned to obligor $i$. Also, let $\rho_1, \ldots, \rho_n \in (0, 1)$ be correlation parameters calibrated to market data where, for Gaussian processes, the pairwise correlation between obligors’ asset values is equal to $\sqrt{\rho_i \rho_j}$. Then, the conditional expectation of portfolio credit loss is given by

$$\mathbb{E}[\mathcal{L}_n | Y = y] = \sum_{i=1}^{n} \delta_i \eta_i \Phi\left(\frac{\Phi^{-1}(\rho_i p_i) - \sqrt{\rho_i} y}{\sqrt{1-\rho_i}}\right), \quad (2.3)$$

where function $p_i(y)$ transforms $p_i$, the unconditional probability of default of obligor $i$, into the probability of default (PD) conditional on realisation $y \in \mathbb{R}$ of systematic risk factor $Y$, or conditional probability of default of obligor $i$. This function, derived by Vasicek (2002), is the kernel of the model specification of the IRB approach. We remark that conditional expectation function $\mathbb{E}[\mathcal{L}_n | Y]$ is strictly decreasing in $y$ — conditional expectation of portfolio credit loss falls (respectively, rises) as the economy improves (deteriorates). Thus, the $\alpha$ quantile of the distribution of $\mathbb{E}[\mathcal{L}_n | Y]$ is associated with the $(1-\alpha)$ quantile of the distribution of $Y$.

Expected portfolio credit loss is the average loss over all realisations $y \in \mathbb{R}$ of systematic risk factor $Y$, defined as

$$\mathbb{E}[\mathcal{L}_n] = \sum_{i=1}^{n} \delta_i \eta_i p_i. \quad (2.4)$$
In keeping with the Basel II Accord (Basel Committee on Banking Supervision, 2006), we define unexpected loss on a credit portfolio as the difference between \( \text{VaR}_\alpha(L_n) \) and \( \mathbb{E}[L_n] \). Furthermore, we assume that ADIs set aside provisions for absorbing expected losses, and hold capital against unexpected losses. This latter assumption is consistent with the prudential standards of APRA (2008). Appealing to Gordy’s proposition, we substitute \( \mathbb{E}[L_n | Y = \Phi^{-1}(1-\alpha)] \) for \( \text{VaR}_\alpha(L_n) \). Hence, at the \( \alpha \) confidence level over a given risk measurement horizon, capital held against unexpected credit losses on a portfolio comprising \( n \) obligors is calculated as

\[
K_\alpha(L_n) = \mathbb{E}[L_n | Y = \Phi^{-1}(1-\alpha)] - \mathbb{E}[L_n] = \sum_{i=1}^{n} \delta_i \eta_i \Phi\left(\frac{\Phi^{-1}(p_i) - \sqrt{p_i} \Phi^{-1}(1-\alpha)}{\sqrt{1-p_i}}\right) - \sum_{i=1}^{n} \delta_i \eta_i p_i \\
= \sum_{i=1}^{n} \delta_i \eta_i \Phi\left(\frac{\Phi^{-1}(p_i) + \sqrt{p_i} \Phi^{-1}(\alpha)}{\sqrt{1-p_i}}\right) - \sum_{i=1}^{n} \delta_i \eta_i p_i. \tag{2.5}
\]

The last equality follows from the symmetry of the standard Gaussian density function.

Under the IRB approach developed by the Basel Committee on Banking Supervision (BCBS), regulatory capital is determined at the 99.9% confidence level over a one-year horizon — a 0.1% probability that credit losses will exceed provisions and capital over the subsequent year. In practice, it incorporates a maturity adjustment, denoted \( \nu_i \), to account for the greater likelihood of downgrades for longer-term claims, the effects of which are stronger for claims with higher credit ratings. Thus, regulatory capital for a portfolio comprising \( n \) obligors reduces to

\[
K_{99.9\%}(L_n) = \sum_{i=1}^{n} \delta_i \eta_i \nu_i \Phi\left(\frac{\Phi^{-1}(p_i) + \sqrt{p_i} \Phi^{-1}(0.999)}{\sqrt{1-p_i}}\right) - \sum_{i=1}^{n} \delta_i \eta_i \nu_i p_i. \tag{2.6}
\]

BCBS (2005) claims that the IRB approach sets regulatory capital for credit risk at a level where losses exceed it, “on average, once in a thousand years.” Qualifying this informal statement of probability, BCBS cautions that the 99.9% confidence level was chosen because tier 2 capital “does not have the loss absorbing capacity of tier 1”, and “to protect against estimation error” in model inputs as well as “other model uncertainties.” With provisions and capital amounting to as little as 2.0–3.0% of EAD under the IRB approach, perhaps the claim of protection against insolvency due to credit losses at the 99.9% confidence level should be interpreted as providing a margin for misspecification of the ASRF model, and not literally protection against a “one in a thousand year” event. The choice of confidence level for the ASRF model may also have been influenced by the desire to produce regulatory capital requirements that are uncontroversial vis-à-vis Basel I. These qualifying remarks warn against the complacency engendered by the high confidence level chosen for the IRB approach.

3. **Basel II Capital Adequacy Reporting**

Under its implementation of Basel II, APRA requires ADIs to assess capital adequacy for credit, market and operational risks. ADIs determine regulatory capital for credit risk using either the standardised approach or, subject to approval, the IRB approach. The former applies prescribed risk weights to credit exposures based on asset class and credit rating grade to arrive at an estimate of RWA. Then, the minimum capital requirement is simply 8% of RWA. The standardised approach, which is an extension of Basel I, is straightforward to administer and produces a relatively conservative estimate of regulatory capital. The IRB approach, which implements ASRF model (2.5), is a more sophisticated method requiring more input data estimated at higher precision. Its greater complexity makes it more expensive to administer, but usually produces lower capital requirements than the standardised approach. As a consequence, ADIs using the IRB approach may deploy their capital in pursuit of more (profitable) lending opportunities.
Upon implementation of Basel II in the first quarter of 2008, APRA had granted the four largest Australian banks, designated “major” banks, approval to use the IRB approach to capital adequacy for credit risk. They include: Commonwealth Bank of Australia (CBA), Westpac Banking Corporation (WBC), National Australia Bank (NAB), and Australia and New Zealand Banking Group (ANZ). WBC acquired St. George Bank (STG) on December 1, 2008, and CBA acquired Bank of Western Australia (BWA) on December 19, 2008. Putting them in a global context, all four major Australian banks have been ranked in the top 20 banks in the world by market capitalisation, and top 50 by assets, during 2013. Since the implementation of Basel II, the major banks have accounted for, on average, 74.6% of total assets on the balance sheet of ADIs regulated by APRA. Furthermore, of the regulatory capital reported by the major banks, on average, 88.0% has been assessed for credit risk, 6.9% for operational risk and 4.4% for market risk, with other capital charges applied by APRA accounting for the remaining 0.7%.

Since our empirical analysis evaluates the model specification of the IRB approach by taking readings of the Australian banking sector, we focus on those credit exposures for which regulatory capital charges are assessed by ASRF model (2.6). We aggregate data reported to APRA by the major banks on a quarterly basis from March 31, 2008, through June 30, 2013. Specifically, data reported on the statement of financial performance, capital adequacy form, and IRB credit risk forms Banking book exposures are reported on credit risk forms by IRB asset class: corporate (non-financial), small- and medium-sized enterprises (SME), bank, sovereign, residential mortgages, retail qualified revolving, and other retail. For presentation purposes we merge IRB asset classes, and report credit exposures as business, government or household. Henceforth, we

1 Average of figures for quarters ending March 31, 2008, through June 30, 2013, published by APRA (2013) in its quarterly issue of ADI performance statistics.
2 Data are reported for the major Australian banks, in aggregate, so as not to violate confidentiality agreements.
3 NAB did not adopt the IRB approach to capital adequacy for credit risk until the second quarter of 2008. Therefore, in measuring the effect of the financial crisis, we omit NAB from our major banks’ aggregate for the quarter ending March 31, 2008.
4 For a number of quarters after the acquisitions of BWA and STG by CBA and WBC, respectively, BWA and STG reported credit risk using the IRB approach in parallel with the consolidated reporting of CBA and WBC, which determined RWA for credit risk in the banking books of BWA and STG using the standardised approach. In our analysis we have included the parallel IRB credit risk forms submitted by BWA and STG, and deducted the corresponding RWA, as determined by the standardised approach, from the consolidated RWA reported by CBA and WBC, respectively.

Figure 1. EAD and RWA by sector for IRB credit exposures of the major Australian banks.

Source: Australian Prudential Regulation Authority.
refer to these banking book exposures as IRB credit exposures. Figure 1 decomposes EAD and RWA, respectively, for IRB credit exposures into business, government and household sectors. Since the implementation of Basel II, RWA for credit risk reported by the major Australian banks has been divided, on average, 71.9/28.1 between IRB credit exposures and other banking book exposures. The market dominance of the major banks, coupled with the concentration of their capital held against unexpected losses on IRB credit exposures, convey the significance of the ASRF model in protecting the Australian banking sector against insolvency. Accordingly, we contend that, while focusing exclusively on IRB credit exposures of the major banks, our empirical analysis draws a representative sample of the credit risk assumed by the Australian banking sector.

Under the IRB approach ADIs assign internally-defined obligor grades reflecting PD bands to their on- and off-balance sheet credit exposures. Between 2008 and 2013 RWA for the IRB credit exposures held in the banking book of the major Australian banks has been divided, on average, 75.4/24.6 between on-balance sheet assets and off-balance sheet exposures. EAD, RWA, expected loss, and exposure weighted LGD, unconditional PD, maturity and firm size are reported for each obligor grade. We assign IRB credit exposures reported by the major banks to standardised PD bands (i.e., consistent across the major banks), and calculate risk parameters characterising each of these standardised obligor grades. The ASRF model incorporates a maturity adjustment, which is a function of maturity and unconditional PD, for business and government credit exposures. Asset correlation is constant for residential mortgages and retail qualified revolving credit exposures; a function of unconditional PD for corporate, bank, sovereign and other retail credit exposures; and a function of firm size and unconditional PD for SME credit exposures (Basel Committee on Banking Supervision, 2005). We constitute a commingled credit portfolio by pooling obligor grades across IRB asset classes.

RWA, capital and provisions are reported on the capital adequacy form. RWA are reported by risk class, and within the credit risk class, for IRB asset classes and the standardised approach. These data are aggregated across capital adequacy forms submitted by the major Australian banks.

**Figure 2.** Capital as a percentage of RWA for the major Australian banks.
Source: Australian Prudential Regulation Authority.
banks. Note that the minimum capital requirement is simply 8% of RWA. Then, subject to a minimum 8% of RWA, APRA sets a prudential capital ratio for each ADI, and an ADI typically holds a capital buffer above its prudential capital requirement (Australian Prudential Regulation Authority, 2007). Figure 2 decomposes the aggregate capital base of the major banks, measured as a percentage of RWA, into tier 1 and tier 2 capital.

Finally, we take credit losses as charges for bad and doubtful debts reported on the statement of financial performance, or income statement. Credit losses are aggregated across income statements reported to APRA by the major banks.

4. Recent Performance of the Australian Economy

In conducting our evaluation of the model specification of the Basel II IRB approach, we use internal bank data collected by APRA to solve for realisations of the single systematic risk factor describing the prevailing state of the Australian economy. These readings of the Australian banking sector are then compared with signals from macroeconomic indicators and financial statistics to render our assessment. Here, we describe the performance of the Australian economy over the past decade, a period which includes the financial crisis of 2007–09, also known as the global financial crisis. While the crisis precipitated the worst global recession since the Great Depression, its effects were not evenly felt across the globe. In order to contextualise the Australian economy we compare its performance with those of the United States and United Kingdom, economies that experienced the full force of the recent crisis. The resilience of the Australian economy to the crisis is evident from a review of macroeconomic indicators and financial statistics that portend or reflect credit stresses: real GDP growth, unemployment rate, house prices, and return on equity of the banking sector.

A number of explanations for the resilience of the Australian economy have been proffered:

- Since the mid 2000s Australia has benefited from a favourable movement in terms of trade driven by the strong global demand for commodities, much of it coming from Asia. An appreciating foreign exchange rate over the same period has been a key factor in the relatively smooth adjustment of the economy to the increase in terms of trade (Bishop et al., 2013). Inflation has been consistent with the target set by the Reserve Bank of Australia (RBA), unemployment has remained relatively low, and economic growth has mostly been around trend — the economy registered a mild contraction in the fourth quarter of 2008, but did not experience a recession. These economic fundamentals have shielded Australia from the financial crisis.

- Residential mortgages, typically floating rate with full recourse to the borrower, have accounted for 50–60% of loans on the balance sheet of Australian banks over the past decade. With the vast bulk of residential mortgages originated by the banks and held to maturity, the risks associated with the banks’ residential mortgage portfolios are comparatively small. Other notable structural factors of the Australian financial sector which serve to constrain excessive risk taking include: the government’s “four pillars” policy precluding mergers between the four major banks, which dominate the Australian financial sector; and the ability of the Australian banks to pay fully-franked dividends to shareholders (Lewis, 2013). The attention to risk quantification and management by the major banks, in order to achieve Basel II IRB approval in 2008, arguably helped discourage excessive risk-taking too (Brown and Davis, 2010).

- APRA, which is responsible for the regulation of deposit-taking institutions, insurance companies and superannuation funds, distinguishes prudential supervision in Australia by its active, risk-based approach (Lewis, 2013). BCBS (2012) calls for greater focus

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5 Measures of financial position (stocks) and performance (flows), national and company level.
Figure 3. Macroeconomic performance of Australia vis-à-vis that of the United States and United Kingdom.

Sources: Australian Bureau of Statistics; Australian Prudential Regulation Authority; US Bureau of Economic Analysis; US Bureau of Labor Statistics; US Federal Reserve Economic Data; Standard & Poor’s; UK Office of National Statistics.

-2.5 -2.0 -1.5 -1.0 -0.5 0.0 0.5 1.0 1.5 2.0 2.5

2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
% Real GDP growth

Australia
United States
United Kingdom

-2.5 0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 20.0 22.5

2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
% House price index

Australia
United States
United Kingdom

on risk-based supervision in its core principles for effective banking supervision: “[t]his risk-based process targets supervisory resources where they can be utilised to the best effect, focussing on outcomes as well as processes, moving beyond passive assessment of compliance rules.” There were significant failures of non-bank financial companies during the financial crisis with investors, rather than taxpayers, bearing the losses. The list of failed companies includes: Absolute Capital, Allco Finance Group, Babcock and Brown, Opes Prime, RAMS Home Loans and Storm Financial. Australia’s banking sector, on the other hand, experienced no failures. Indeed, while banks’ profitability declined during the crisis, it remained quite healthy. Also, the major Australian banks maintained their AA credit rating through the crisis (Brown and Davis, 2010; D’Aloisio, 2010).

• In October 2008 the Australian government introduced two schemes, announced with a three-year duration, to guarantee bank funding. Under the Financial Claims Scheme, all deposits up to $1 million with locally-incorporated ADIs were automatically guaranteed by the government with no fee payable. Under the Funding Guarantee Scheme, the government provided a guarantee, for a fee, on deposits over $1 million and wholesale funding with maturity out to five years. The RBA believes that these schemes achieved their goal of maintaining public confidence in the Australian banking sector (Senate Standing Committees on Economics, 2011).
• At the onset of the financial crisis, in October 2007, the RBA sought to restore liquidity to dysfunctional credit markets by expanding the range of securities it would accept as collateral for repurchase agreements to include residential mortgage-backed securities and asset-backed commercial paper (Debelle, 2007). Then, as the crisis spread to the real economy, the RBA slashed its target cash rate from 7.25% in August 2008 to 3.0% in April 2009. Importantly, much of the monetary policy easing was passed through to borrowers. With most household and business loans in Australia being variable, lower interest rates translated into higher disposable incomes. Falling interest rates coupled with rising incomes improved housing affordability somewhat, and helped avert a sharp correction in the housing market, which had boomed over the previous decade (McDonald and Morling, 2011).

• Between October 2008 and February 2009 the Australian government announced substantial fiscal stimulus packages: $10.4 billion Economic Security Strategy; $15.2 billion Council of Australian Governments funding package; $4.7 billion Nation Building package; and $42 billion Nation Building and Jobs Plan. The Treasury estimates that, absent the fiscal stimulus, GDP growth would have been negative for three consecutive quarters (McDonald and Morling, 2011).

• Finally, the “lucky” country was probably not without a dose of good fortune. The charts in Figure 3 clearly indicate that the Australian economy was largely cushioned from the adverse effects of the recent crisis.

5. Measurements from the ASRF Model of the Australian Banking Sector

The Basel II IRB approach implements ASRF model (2.6), an asset value factor model. Other asset value models include: Moody’s KMV, RiskMetrics, and most internal bank models. They too are generally factor models. Note that multi-factor asset value models typically express asset values as a function of a composite factor obtained by the superposition of underlying independent risk indices (Bluhm et al., 2010). We believe that our empirical findings are applicable to the broader class of asset value factor models of credit risk.

Applying the ASRF model prescribed by the IRB approach to internal bank data collected by APRA, our empirical analysis generates time series of: (i) the single systematic risk factor describing the prevailing state of Australia’s economy; and (ii) distance to default measuring the capacity of its banking sector to absorb credit losses. Then, comparing these time series with macroeconomic indicators, financial statistics and external credit ratings we render our assessment of the model specification of the IRB approach. Furthermore, since the depths of the financial crisis of 2007–09 were reached after the implementation of Basel II, these results offer a fundamental evaluation of the impact of the crisis on the Australian banking sector. To our knowledge other studies on the recent crisis have relied on public information — market data, macroeconomic indicators or published financial statistics — to measure its effects. Access to internal bank data collected by the prudential regulator distinguishes our research from other empirical studies.

Taking measurements from the ASRF model of the Australian banking sector requires data reported on IRB credit risk forms, which are available for the major banks since the first quarter of 2008 on a quarterly basis. Recall that IRB credit risk forms assign credit exposures to an obligor grade identifying a PD band within an IRB asset class. Pooling obligor grades, reported as at the end of a given quarter, across IRB asset classes constitutes a commingled credit portfolio in which each obligor grade is represented as a single credit. The quarterly observations between March 31, 2008, and June 30, 2013, establish a time series of commingled credit portfolios.
Prudential standards published by APRA instruct ADIs to assign one-year unconditional (through-the-cycle) PDs to IRB credit exposures. Accordingly, credit risk parameters and variables reported as at the end of a given quarter are used to make projections of credit losses incurred over the subsequent four quarters. Recall that \( \delta_i(t), \eta_i(t), \nu_i(t), p_i(t) \) and \( \rho_i(t) \) denote the EAD, LGD, maturity adjustment, unconditional PD and asset correlation assigned to credit \( i \) as at the end of quarter \( t \). They are input to the ASRF model, which makes projections of losses on IRB credit exposures over a one-year horizon.

5.1. Prevailing State of the Australian Economy. The ASRF model prescribed by IRB approach assesses regulatory capital charges by calculating the expectation of credit losses conditional on a realisation of the single systematic risk factor. Substituting losses incurred on IRB credit exposures into the ASRF model, we recover realisations of the single systematic risk factor describing states of the Australian economy experienced since the implementation of Basel II. Then, applying the standard Gaussian distribution function yields the quantile of the distribution of economic scenarios.

For any one-year horizon over which the ASRF model makes projections of credit losses, we choose to associate the model inputs with the realisation of the single systematic risk factor as at the midpoint of the corresponding risk measurement horizon. So, measuring time in quarterly increments, realisation \( y(t) \) of systematic risk factor \( Y \) describing the state of the economy as at the end of quarter \( t \) is associated with credit losses projected over the time interval \([t-1, t+2] \) using credit risk parameters and variables reported as at the end of quarter \( t-2 \).

Suppose that for each quarter in the time series, there is a total of \( r \) banking book exposures subject to credit risk, of which \( n \) IRB credit exposures are held in the aforementioned commingled portfolio, where \( n \leq r \). Denote by \( R_n(t), R_r(t) \) and \( R(t) \) the RWA for IRB credit exposures, RWA for credit risk and total RWA, respectively, as at the end of quarter \( t \). Also, let \( L_r(s) \) be the total credit losses incurred during quarter \( s \). We do not observe \( L_n(s) \), losses incurred on IRB credit exposures during quarter \( s \). Therefore, we choose to allocate total credit losses incurred during the four-quarter interval \([s-1, s+2] \) between IRB credit exposures and other banking book exposures in proportion to RWA as at the end of the quarter \( t-2 \). So, losses on IRB credit exposures incurred during quarters \( s-1, s+1 \) and \( s+2 \) is given by

\[
\frac{R_n(t-2)}{R_r(t-2)} (L_r(s-1) + L_r(s) + L_r(s+1) + L_r(s+2)). \tag{5.1}
\]

In taking measurements from the ASRF model of the Australian banking sector, we assume that there is no delay in the recognition of bad debts. (Later, we allow for delays in the recognition of bad debts.) Setting \( s = t \), projected credit losses over any one-year horizon are compared with credit losses incurred during the same one-year interval. Then, applying the formula for conditional expectation of portfolio credit losses:

\[
\frac{R_n(t-2)}{R_r(t-2)} (L_r(t-1) + L_r(t) + L_r(t+1) + L_r(t+2))
= \sum_{i=1}^{n} \delta_i(t-2) \eta_i(t-2) \nu_i(t-2) \Phi \left( \frac{\Phi^{-1}(p_i(t-2)) - \sqrt{\rho_i(t-2)} y(t)}{\sqrt{1 - \rho_i(t-2)}} \right), \tag{5.2}
\]

we solve for realisation \( y(t) \) of systematic risk factor \( Y \). Repeating this static analysis for each quarter \( t \) from September 30, 2008, through December 31, 2012, generates a time series of systematic risk factor \( Y \). The ASRF model assumes that the conditional expectation of portfolio credit losses rises as the economy deteriorates — a strictly decreasing function of the single systematic risk factor. By convention the \( \alpha \) quantile of the distribution of \( \mathbb{E}[L_n | Y] \) is associated with the \( 1 - \alpha \) quantile of the distribution of \( Y \). Hence, confidence level \( \alpha(t) \) corresponding to
Figure 4. Realisations $y(t)$ of systematic risk factor $Y$ describing the prevailing state of the Australian economy and real GDP growth, y-o-y.

Source: Australian Bureau of Statistics.

Realisation $y(t)$ of systematic risk factor $Y$ is given by

$$\alpha(t) = 1 - \Phi(y(t)). \quad (5.3)$$

Real GDP growth, plotted for the Australian economy in Figure 3, is conventionally reported as seasonally adjusted, quarter-over-quarter. Quarterly realisations of the single systematic risk factor are recovered by equating credit losses projected over a one-year horizon with credit losses incurred during the same one-year interval. Accordingly, we restate quarterly observations of real GDP growth for the Australian economy as year-over-year. Figure 4 plots time series of the single systematic risk factor describing the prevailing state of the Australian economy and real GDP growth, year-over-year. The time series are quite strongly correlated (+0.60), suggesting that the single systematic risk factor serves as a reasonable proxy for the relative state of the economy. Indeed the correlation between the time series rises to +0.72 when realisations of the single systematic risk factor are lagged by one or two quarters. Arguably, realisation $y(t)$ of systematic risk factor $Y$ leads real GDP growth, but realisation $y(t)$ cannot be computed until credit losses $L_r(t+2)$ are recognised in profit and loss for quarter $t+2$.

To assess whether the single systematic risk factor provides a reasonable proxy of the absolute state of the economy, we take readings at the depths of the financial crisis. Figure 5 plots the impact of the crisis on the credit portfolios of the major Australian banks in terms of the single systematic risk factor. Bear in mind that measurements from the ASRF model of the Australian banking sector capture policy responses of government departments and agencies (i.e., The Treasury, RBA and APRA) designed to mitigate the recent crisis. Naturally, it is not possible to isolate these policy responses in order to ascribe a value to their mitigating effects. In light of this qualification, the results suggest that the economic shock imparted by the financial crisis propagated through the Australian banking system inflicting credit losses incurred,
Figure 5. Impact of the financial crisis of 2007–09 on the credit portfolios of the major Australian banks. Realisation $y$ of systematic risk factor $Y$ describes the prevailing state of the economy. Confidence level $\alpha$ is the probability of the state of the economy being better than the economic scenario described by realisation $y$.

(a) Credit losses are allocated between IRB credit exposures and other banking book exposures in proportion to RWA.
(b) Credit losses are allocated entirely to IRB credit exposures providing a lower bound on $Y$.

-1.25 -1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00 1.25
Dec-08 Jun-09 Dec-09 Jun-10 Dec-10 Jun-11 Dec-11 Jun-12

90 84 77 69 60 50 40 31 23 16

Systematic risk factor $Y$

Confidence level $\alpha$, %

on average, once every five years. Even if credit losses were attributed entirely to IRB credit exposures, the crisis would have inflicted credit losses not exceeding those incurred, on average, once every eight years — a lower bound on the severity of the crisis in Australia. This is consistent with the perception that Australian banks weathered the recent crisis quite well, reporting good profitability and high capital ratios, and maintaining strong credit ratings. Overall, the time series of the prevailing state of the economy agrees rather well with the macroeconomic indicators and financial statistics plotted in Figure 3.

The prevailing state of the economy at the depths of the crisis, as recovered from the ASRF model, is summarised by realisation $y = -0.81$ on December 31, 2008. Appealing to Gordy’s proposition, $y = -0.81$ translates into the 79.1% quantile of the portfolio loss distribution — credit losses incurred were no greater than expected in 79.1% of economic scenarios, or approximately one in five years. We argue that the single systematic risk factor is a germane measure of the effect of the financial crisis, because the IRB approach chooses realisation $y = -3.090$ of systematic risk factor $Y$ to assess regulatory capital charges that are expected to absorb credit losses in 99.9% of economic scenarios.

The model specification of the IRB approach was developed for the purpose of solvency assessment, or capital adequacy. A credit risk model of capital adequacy requires precision in the
measurement of absolute risk levels under stressed economic conditions associated with the tail of the portfolio loss distribution (Basel Committee on Banking Supervision et al., 2010). Recognising that realisations of the single systematic risk factor describing states of the Australian economy experienced since the implementation of Basel II correspond to observations away from the tail of its distribution, we cannot attest to the validity of the ASRF model for regulatory capital modelling. However, we argue that our findings support a favourable assessment of the ASRF model, and asset value factor models of credit risk in general, for the purposes of capital allocation, performance attribution and risk monitoring. These management functions, generally served by economic capital models, need only be accurate in the measurement of relative risk under “normal” economic conditions.

It could be argued that delays in the recognition of bad debts warrant introducing a lag in the association of projected credit losses with credit losses incurred. Figure 6 plots the time series of the prevailing state of the economy (i.e., realisations of the single systematic risk factor) assuming no delay in the recognition of bad debts ($s = t$), along with time series assuming delays of one quarter ($s = t + 1$) and two quarters ($s = t + 2$). Introducing lags to account for possible delays in the recognition of bad debts does not materially alter our measurement of the impact of the financial crisis on the credit portfolios of the major Australian banks at the depths of the crisis — it remains a one in five year event.

This empirical analysis begins with the initial submission of capital adequacy and IRB credit risk forms as at March 31, 2008, and credit losses recognised in profit and loss between April 1,
2008, and March 31, 2009, and solves for the single systematic risk factor describing the state of the economy as at September 30, 2008. Our measurement of the impact of the financial crisis on the Australian banking sector is necessarily predicated on the assumption that the effect of the crisis was most acutely felt after March 31, 2008. Figure 7 indicates that credit losses incurred by the major Australian banks peaked in the fourth quarter of 2008 and remained elevated through 2009, and global equity indices plumbed their lows during the first quarter of 2009 — S&P ASX 200 index fell 54% between November 2007 and March 2009.

Our measurement of the impact of the financial crisis on the Australian banking sector is buttressed by the macroeconomic stress test administered by APRA on the major Australian banks in 2012. The three-year economic scenario developed for the stress test by APRA in conjunction with the RBA and Reserve Bank of New Zealand, was designed to be comparable with the actual experience of the United States and United Kingdom during the recent crisis. In particular, the macroeconomic stress test envisaged: real GDP contracting 5%; unemployment rising to 12%; house prices falling 35%; and commercial property prices falling 40%. None of the major Australian banks would have failed under this severe but plausible economic scenario, nor would any of the major banks have breached the 4% minimum tier 1 capital requirement of the Basel II Accord (Laker, 2012).

5.2. Australian Banks’ Capacity to Absorb Credit Losses. Distance to default, which measures the level of capitalisation, reflects the capacity to absorb credit losses. Substituting provisions set aside for absorbing expected losses and capital held against unexpected losses on IRB credit exposures into the ASRF model, and translating realisations of the single systematic risk factor into distance to default, we measure the level of capitalisation of the major Australian banks, in aggregate since the implementation of Basel II.

Suppose that a bank sets aside provisions and holds capital that are sufficient to absorb credit losses at the $\alpha$ confidence level. Denote by $Q_r(t)$ provisions set aside for absorbing expected credit losses as at the end of quarter $t$, and $K(t)$ the capital base as at the end of quarter $t$. Recall that APRA sets a prudential capital ratio, subject to a minimum 8% of RWA, for each ADI, and an ADI typically holds a capital buffer above its prudential capital requirement. Since we observe neither provisions set aside for absorbing expected losses nor capital held against unexpected losses on IRB credit exposures, we choose an allocation procedure. Provisions are allocated between IRB credit exposures and other banking book exposures in proportion to

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6 Results are reported for the major Australian banks, in aggregate, so as not to violate confidentiality agreements.
expected losses over the subsequent four quarters as projected at the end of quarter $t$:

$$Q_n(t) = \frac{\mathbb{E}[L_{n}(t+1) + L_{n}(t+2) + L_{n}(t+3) + L_{n}(t+4)]}{\mathbb{E}[L_r(t+1) + L_r(t+2) + L_r(t+3) + L_r(t+4)]} Q_r(t). \quad (5.4)$$

Capital is allocated between IRB credit exposures and other risk exposures (i.e., non-IRB credit exposures, and operational, market and securitisation risks) in proportion to RWA as at the end of quarter $t$:

$$\kappa_n(t) = \frac{R_n(t)}{R(t)} \kappa(t). \quad (5.5)$$

Hence, provisions set aside for absorbing expected losses and capital held against unexpected losses on IRB credit exposures as at the end of quarter $t$ is equal to $Q_n(t) + \kappa_n(t)$. Assuming that the major banks report unconditional (through-the-cycle) PDs in their submissions to APRA, we solve for realisation $\tilde{y}(t)$ of systematic risk factor $Y$ that equates the sum of (5.4) and (5.5) to the conditional expectation of portfolio credit losses:

$$Q_n(t) + \kappa_n(t) = \sum_{i=1}^{n} \delta_i(t) \eta_i(t) \nu_i(t) \Phi \left( \frac{\Phi^{-1}(p_i(t)) - \sqrt{1 - \rho_i(t)} \tilde{y}(t)}{\sqrt{1 - \rho_i(t)}} \right). \quad (5.6)$$

Note that the sum of provisions set aside for absorbing expected credit losses and capital held against unexpected credit losses in (5.6), replaces the sum of expected losses and regulatory capital in ASRF model (5.5). Denote by $\tilde{d}(t)$ the distance to default as at the end of quarter $t$. Then,

$$\tilde{d}(t) = -\tilde{y}(t), \quad (5.7)$$

which translates into confidence level

$$\tilde{\alpha}(t) = 1 - \Phi(-\tilde{d}(t)) = \Phi(\tilde{d}(t)). \quad (5.8)$$

It follows from (5.5) that the risk-based capital ratio as at the end of quarter $t$, plotted in Figure 2, is given by

$$\kappa(t) = \frac{\kappa(t)}{R(t)} = \frac{\kappa_n(t)}{R_n(t)} \quad (5.9)$$

Table I reports quarterly risk-based capital ratio for the major banks, in aggregate, along with implied distance to default. Since 2008 they have maintained a capital base that is consistent with targeting a credit rating between A and AA (i.e., a target confidence level between 99.96% and 99.99%). Note that, under the prudential standards of APRA (2008), if provisions set aside are insufficient to absorb expected credit losses, the shortfall is deducted from capital. The general agreement of our estimates of distance to default with credit ratings issued by external rating agencies seemingly lends further support to a favourable assessment of the model specification of the IRB approach. However, distance to default is a measure of capital adequacy, and Section 5.1 argues that we cannot attest to the suitability of the ASRF model for the purpose of solvency assessment, because realisations of the single systematic risk factor experienced in Australia since the implementation of Basel II correspond to observations away from the tail of its distribution. Therefore, we report estimates of distance to default with the caveat that (5.5) models default dependence in the tail of the portfolio loss distribution as a multivariate Gaussian process.

In contrast to our evaluation of the capacity of the major banks to absorb credit losses during the financial crisis, Allen and Powell (2012) argue that Australian banks did not fare much better than their global counterparts. They compare the distance to default of the Australian banking sector with that of the banking sectors in the United States, Europe and Canada. In their implementation of the KMV/Merton structural methodology, distance to default is a function of implied market value and volatility of assets imputed from equity prices. Allen and Powell observe that the distance to default for Australian banks narrowed sharply from a peak of 11.31 in
Table 1. As reported risk-based capital ratio $\kappa(t)$, and implied distance to default $\tilde{d}(t)$ for the major Australian banks, in aggregate. The reverse stress test uncovers the weakest economic shock $\hat{y}(t)$ that would result in a breach of the capital ratio floor $\kappa$. Realisation $y(t)$ describes the prevailing state of the economy.

| $t$            | $\kappa(t)$, % | $\tilde{d}(t)$ | $\hat{y}(t)$, % | $\alpha(t)$, % | $\kappa = 4.0\%$ | $\alpha(t)$, % | $\kappa = 8.0\%$ | $\alpha(t)$, % | $y(t)$, % | $\alpha(t)$, % |
|----------------|----------------|----------------|-----------------|----------------|------------------|----------------|------------------|----------------|-----------|----------------|
| 31-Mar-2008    | 10.67          | 3.504          | 99.977          |                |                  |                |                  |                | 10.67     | 99.977         |
| 30-Jun-2008    | 10.73          | 3.413          | 99.968          |                |                  |                |                  |                | 10.73     | 99.968         |
| 30-Sep-2008    | 10.98          | 3.508          | 99.978          |                |                  |                |                  |                | 10.98     | 99.978         |
| 31-Dec-2008    | 11.51          | 3.588          | 99.983          |                |                  |                |                  |                | 11.51     | 99.983         |
| 31-Mar-2009    | 11.38          | 3.621          | 99.985          |                |                  |                |                  |                | 11.38     | 99.985         |
| 30-Jun-2009    | 11.10          | 3.620          | 99.985          |                |                  |                |                  |                | 11.10     | 99.985         |
| 30-Sep-2009    | 11.52          | 3.682          | 99.988          |                |                  |                |                  |                | 11.52     | 99.988         |
| 31-Dec-2009    | 11.85          | 3.732          | 99.991          |                |                  |                |                  |                | 11.85     | 99.991         |
| 31-Mar-2010    | 11.82          | 3.717          | 99.990          |                |                  |                |                  |                | 11.82     | 99.990         |
| 30-Jun-2010    | 11.51          | 3.677          | 99.988          |                |                  |                |                  |                | 11.51     | 99.988         |
| 30-Sep-2010    | 11.50          | 3.690          | 99.988          |                |                  |                |                  |                | 11.50     | 99.988         |
| 31-Dec-2010    | 11.27          | 3.653          | 99.987          |                |                  |                |                  |                | 11.27     | 99.987         |
| 31-Mar-2011    | 11.49          | 3.682          | 99.989          |                |                  |                |                  |                | 11.49     | 99.989         |
| 30-Jun-2011    | 11.42          | 3.660          | 99.987          |                |                  |                |                  |                | 11.42     | 99.987         |
| 30-Sep-2011    | 11.48          | 3.647          | 99.987          |                |                  |                |                  |                | 11.48     | 99.987         |
| 31-Dec-2011    | 11.42          | 3.642          | 99.986          |                |                  |                |                  |                | 11.42     | 99.986         |
| 31-Mar-2012    | 11.48          | 3.637          | 99.986          |                |                  |                |                  |                | 11.48     | 99.986         |
| 30-Jun-2012    | 11.44          | 3.633          | 99.986          |                |                  |                |                  |                | 11.44     | 99.986         |
| 30-Sep-2012    | 11.72          | 3.659          | 99.987          |                |                  |                |                  |                | 11.72     | 99.987         |
| 31-Dec-2012    | 11.75          | 3.663          | 99.988          |                |                  |                |                  |                | 11.75     | 99.988         |
| 31-Mar-2013    | 11.69          | 3.698          | 99.989          |                |                  |                |                  |                | 11.69     | 99.989         |
| 30-Jun-2013    | 11.42          | 3.657          | 99.987          |                |                  |                |                  |                | 11.42     | 99.987         |
Note that a distance to default of 0.60 translates into roughly a one-in-four chance of bank failure, but in reality there were none. An implicit assumption of their analysis is that security markets consistently price risk fairly. But it’s not uncommon for markets to exhibit bouts of manic-depressive behaviour. During periods when market participants are gripped by fear (respectively, driven by greed), their perception of risk is heightened (lessened), and markets become undervalued (overpriced). We submit that their results are biased by plummeting equity prices and spiking volatility reflecting the overreaction of market participants gripped by fear at the depths of the crisis — the S&P ASX 200 Banks index fell 58% between November 2007 and January 2009. With access to internal bank data collected by APRA, we produce a fundamental evaluation of the effect of the recent crisis and solvency of Australian banks that differs markedly from the stock market’s assessment.

5.3. Reverse Stress Testing. Stress testing is an important risk management tool promoted by supervisors through the Basel II framework. Indeed, banks using the IRB approach to capital adequacy for credit risk are required to conduct stress tests to examine the robustness of their internal capital adequacy assessments. In its principles for sound stress testing, BCBS (2009) recommends that supervisors make regular and comprehensive assessments of banks’ stress testing programs, and encourages supervisors to conduct stress tests based on common scenarios for banks in their jurisdiction. Usually, a stress test begins with the development of an economic scenario that is the manifestation of some stress event or economic shock. It is then translated into conditional (point-in-time) PDs assigned to obligors constituting a bank’s credit portfolio. Finally, an analytical or simulation model estimates portfolio credit losses subject to the stress event, which are charged against provisions and capital to produce an assessment of the bank’s solvency. A variation on this methodology is reverse stress testing — a technique in which “losses that would render an institution unviable or subject to material regulatory intervention are identified and attention then focussed on the types of scenarios that would generate these losses” (Laker, 2010).

Clearly, realisation \( \hat{y}(t) = -\hat{d}(t) \), recovered from (5.6), describes an economic scenario that would render the major banks, in aggregate, insolvent at the end of quarter \( t \) if the associated credit losses were incurred and recognised instantaneously. We extend this rudimentary form of reverse stress testing to uncover economic scenarios that would cause the major banks to breach some designated capital ratio floor \( \kappa \), and consequently trigger supervisory intervention. Suppose that the expectation of portfolio credit losses conditional on stress event \( \hat{y}(t) \) is instantaneously incurred and recognised in profit and loss at the end of quarter \( t \). Then, the capital ratio floor would be breached at the end of quarter \( t \) if credit losses exceeded

\[
Q_n(t) + K_n(t) - \kappa R_n(t).
\]

Economic scenarios worse than that described by realisation \( \hat{y}(t) \) of systematic risk factor \( Y \) satisfying (5.11) would result in a breach of the capital ratio floor at the end of quarter \( t \):

\[
Q_n(t) + K_n(t) - \kappa R_n(t) = \sum_{i=1}^{n} \delta_i(t) \eta_i(t) \nu_i(t) \Phi \left( \frac{\Phi^{-1}(p_i(t)) - \sqrt{\rho_i(t)} \hat{y}(t)}{\sqrt{1 - \rho_i(t)}} \right).
\]

Then, the probability of the state of the economy being better than the economic scenario described by realisation \( \hat{y}(t) \) is a most

\[
\hat{\alpha}(t) = 1 - \Phi(\hat{y}(t)).
\]

Finally, macroeconomic-based models would translate realisations of the single systematic risk factor into observations of macroeconomic indicators (e.g., real GDP growth, unemployment rate, house prices, etc.). This final translation is beyond the scope of this paper.
Our rudimentary stress testing methodology has its limitations: it is static; focuses exclusively on credit risk, assuming away market, liquidity and operational risks; fails to consider diversification benefits or compounding effects arising from the interaction between risk classes; excludes net interest income earned during the period in which credit losses are incurred; and does not consider the possibility of raising fresh capital. Yet it puts the severity of the financial crisis, as experienced by the Australian banking sector, in perspective by comparing it with stress events that would trigger supervisory intervention. Table I reports the weakest economic shock $\hat{y}(t)$ imparted at the end of quarter $t$ that would result in a breach of capital ratio floors set at 4.0% and 8.0% if credit losses were instantaneously incurred and recognised in profit and loss. Section 5.1 made reference to the macroeconomic stress test administered by APRA on the major banks in 2012, describing the severe and plausible economic scenario under which none of the major banks would have breached the 4% minimum tier 1 capital requirement. Table I indicates that with $\kappa = 4.0\%$, approximately 99.9% of economic scenarios, presumably including the severe but plausible one developed for the macroeconomic stress test administrer by APRA, would not have resulted in the major banks, in aggregate, breaching the capital ratio floor in 2012. Even with $\kappa = 8.0\%$, fewer than 1.5% of economic scenarios would have resulted a breach of the capital ratio floor in 2012. During the recent crisis the capacity of the major banks, in aggregate, to absorb credit losses appears to have been “stretched” to the point where 0.22% (respectively, 3.06%) of economic scenarios would have resulted in a breach of the 4.0% (8.0%) capital ratio floor during the quarter ending June 30, 2008. For comparison, Table II also reports the prevailing state of the economy described by quarterly realisations $y(t)$, as plotted in Figure 5.

6. Conclusion

This paper examines the model specification of the Basel II IRB approach. Our empirical analysis takes measurements from the ASRF model of the Australian banking sector, and compares them with signals from macroeconomic indicators, financial statistics and external credit ratings to render an assessment. We believe that our findings are applicable to the broader class of asset value factor models of credit risk. Although, the range of economic conditions, from mild contraction to moderate expansion, experienced in Australia since the implementation of Basel II precludes an evaluation of the ASRF model in the context of solvency assessment. The ASRF model calculates the expectation of credit losses conditional on a realisation of the single systematic risk factor, which is interpreted as describing the state of the economy, in order to assess regulatory capital charges. Substituting credit losses incurred into the ASRF model, we solve for realisations of the single systematic risk factor generating a time series of the prevailing state of the Australian economy since the implementation of Basel II. Its moderately strong correlation with the time series of real GDP growth supports a favourable assessment of the ASRF model for the purposes of capital allocation, performance attribution and risk monitoring. Since the depths of the financial crisis of 2007–09 were reached after the implementation of Basel II, our empirical analysis reveals that the economic shock initiated by the recent crisis propagated through the Australian banking system inflicting credit losses incurred, on average, once every five years. Then, substituting provisions set aside for absorbing expected credit losses and capital held against unexpected credit losses into the ASRF model, and translating realisations of the single systematic risk factor into distances to default, we measure the level of capitalisation of the major Australian banks. In aggregate, they have maintained a capital base that is consistent with credit ratings, between A and AA, issued by external rating agencies. Reverse stress testing, too, reveals that the major banks were adequately capitalised to absorb a substantially more severe shock than the one imparted by the financial crisis. Our fundamental assessment of the impact of the recent crisis on the credit portfolios of the major banks differs
markedly from the stock market’s assessment, which we argue is biased by the overreaction of market participants gripped by fear at the depths of the crisis.

We reiterate that our estimates of the prevailing state of the economy and level of capitalisation of the major banks since the implementation of Basel II are recovered from the ASRF model prescribed by the IRB approach, which models default dependence as a multivariate Gaussian process. However, it is generally acknowledged that models which assume that financial data follow a Gaussian distribution tend to underestimate tail risk. If we were to model default dependence by heavier-tailed distributions, we would find that credit losses incurred at the depths of the financial crisis correspond to a quantile of the portfolio loss distribution further from the tail, and thus associated with a less contractionary, or more expansionary, state of the economy. Also, heavier-tailed distributions would imply a shorter distance to default.

Recognising that realisations of the single systematic risk factor describing states of the Australian economy experienced since the implementation of Basel II correspond to observations away from the tail of its distribution, we cannot attest to the accuracy of the ASRF model in the tail of the portfolio loss distribution, nor its validity for regulatory capital modelling. An evaluation of the model specification of the IRB approach for its intended purpose of solvency assessment would involve taking readings of north Atlantic banking jurisdictions that experienced the full force of the financial crisis. It is unlikely to be as favourable as the qualified evaluation presented in this paper. The UK banking sector, which has operated under the Basel II framework since 2008, experienced losses during the crisis on a scale that led to the failure or nationalisation of large banks including Bradford & Bingley, HBOS, Lloyds Banking Group, Northern Rock and Royal Bank of Scotland. Moreover, the Basel III reform package has been developed by BCBS to address deficiencies of the Basel II framework exposed by the recent crisis. The reforms raise the quality and minimum required level of capital; promote the build up of capital buffers; establish a back-up minimum leverage ratio; improve liquidity and stabilise funding; and apply a regulatory capital surcharge for systemically important financial institutions (Basel Committee on Banking Supervision, 2011).

From our assessment of the model specification of the IRB approach emerges a methodology for regulators to monitor the prevailing state of the economy as described by the single systematic risk factor, and the capacity of supervised banks to absorb credit losses as measured by distance to default. While confidentiality agreements preclude us from publishing results for individual banks, regulators would be at liberty to conduct their analysis on an individual bank basis. Measurements from the ASRF model signalling an overheating economy and procyclical movements in capital bases, corroborated by macroeconomic performance indicators, would prompt supervisory intervention. For example, banks could be instructed to build up countercyclical capital buffers introduced under Basel III in order to rein in rapidly accelerating credit growth. Furthermore, a longer history of the time series of the prevailing state of the economy recovered from the ASRF model could serve to validate and calibrate macroeconomic-based models for estimating conditional (point-in-time) PDs. Macroeconomic-based models for estimating point-in-time PDs usually express the single systematic risk factor as a function of macroeconomic variables and a random economic shock (Chan-Lau, 2006). This time series could also inform the development of economic scenarios for stress testing, a standard tool of prudential supervision.

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