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Commercial Bank Loan Loss Recoveries

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Abstract

We present a new approach to analyse historical recovery rates on distressed bank assets. Our approach uses banks' reported impaired assets and the corresponding specific provisions. The dynamics and drivers of this credit loss recovery proxy are studied for a comprehensive sample of Australian banks from 1989 to 2005. We find that macroeconomic and bank-specific factors influence banks' estimates of loan loss recoveries, consistent with banks smoothing their earnings. In contrast with findings based on prices of distressed corporate bonds, banks record lower recoveries in years of strong economic growth.

Keywords

banking
credit risk
loan loss recoveries
loss given default
Australia

JEL Codes

G20; G21

1. Introduction

The stability of the banking sector is of major importance for economic outcomes. Banks form the backbone of modern economies and instability in the banking sector can pose problems to the economic system as a whole. Credit losses, or more generally, asset quality problems, have repeatedly been identified as a key trigger of bank failures, e.g. Graham and Horner (1988), Caprio and Klingebiel (1996). Accordingly, much research effort has gone into developing methods for assessing credit risk both at a systemic and bank-specific level.

Two major components determine the extent of a credit loss suffered: first, the probability of a default (PD) and, second, the loss given default (LGD), which equals one minus the recovery rate in the event of default. Most credit risk literature has focussed on estimating PD; much less attention has been devoted to estimating characteristics of LGD. We address this lack of research by analyzing the determinants of LGD (or, more specifically, the recovery rate) using a comprehensive sample of Australian banks.

The paucity of research on LGD has been changing in recent years as the new Basel Capital Accord (Basel II) enables banks to employ their own proprietary risk models to calculate capital adequacy. Schuermann (2004) and Altman (2006) provide a comprehensive review of these LGD studies, many of which are authored by rating agencies (e.g. Gupton et al., 2000; Verde, 2003; Keisman, 2004; Moody's Investors Service, 2008). These studies analyse recovery patterns of defaulted corporate bonds; likewise there is research into the recovery of syndicated corporate loans (Asarnow and Marker, 1995; Emery et al., 2004). Results for both corporate bonds and syndicated loans are similar with seniority of the claim and collateralization (secured vs. unsecured lending) impacting the rate of recovery. Given that syndicated loans typically represent senior lending, have stricter covenants and are also mostly secured in the samples studied, their median level of recovery is generally found to be much higher than unsecured bonds.

A related stream of research investigates the correlation between PD and LGD. The consensus of these studies is that there is a negative correlation between the two variables with low (high) recovery rates in times of high (low) defaults (Frye, 2000; Altman et al., 2003; Hu and Perraudin, 2006).

The research into characteristics of LGD is for the most part based on price data of defaulted bonds and in some cases of traded bank loans because such data is readily available. Accordingly, these analyses are not based on comprehensive samples of non-traded loans which represent the bulk of assets for many banks and where there is no market value of distressed debt shortly after default. Nor are they based on realized recoveries but rather assume that market prices are an efficient reflection of the present value of all future recoveries on these claims. Research on actual recoveries exists for traditional, non-traded bank loans but is typically limited to smaller proprietary bank specific data samples (e.g.

Asarnow and Edwards, 1995; Eales and Bosworth, 1998; Araten et al., 2004; Miu and Ozdemir, 2006). In the context of the Basel II implementation, banks have started building their LGD databases but these are not in the public domain. Moreover, anecdotal information indicates that these data typically cover just a few years, and data have not been collected in a consistent and standardized fashion through time.

This paper presents an alternative method for gaining insights into the dynamics of recovery rates for distressed bank lending over longer periods of time, i.e. through economic cycles. Since the late 1980s, banks of most developed countries have reported on the level of loans and other assets considered impaired from a credit risk perspective. Moreover, banks not only report the gross book value of these assets but typically also their expected realizable value thus providing a point in time estimate of overall recovery rates of their total distressed asset portfolio. These values can be interpreted as a proxy for expected recoveries by bank management just as the distressed price based methods represent market expected recovery values of corporate bonds. The main benefit of the method is that recovery estimates are for a representative composition of bank distressed credit exposures rather than the specific bond portfolios of the traditional bond LGD literature. It also enables analysis over longer periods and mirrors outcomes for the whole system, not just a single bank.

We apply the method to explore determinants of recovery rates for a comprehensive panel dataset of 18 Australian banks for the period 1989 to 2005. We consider two groups of explanatory variables. One includes idiosyncratic factors specific to the bank and its risk profile, the other aggregate macroeconomic drivers with systemic impact on asset recoveries. We find that the macroeconomic factors act in the opposite direction for bank loans relative to their effect on corporate bonds found in the traditional distressed price based literature. This latter result implies that banks may use reported recovery rates as a method to smooth their earnings over the cycle. Our estimation utilises three different methods to test robustness of key results.

The paper proceeds as follows. Section 2 describes the data used in the study, including some background on the Australian banking system. Section 3 formulates the hypotheses, and presents the test methodology, empirical results and robustness tests; section 4 concludes.

2. Background and Data

During the period under consideration, the Australian banking system has undergone major structural changes. The 1980s saw the initiation of major sector reforms (Campbell Inquiry, 1981). The various types of financial institutions such as trading banks, savings banks, state banks, trust banks and building societies were initially subject to carefully delineated sets of legislation, but a substantial blurring between their activities had occurred. The liberalization of the financial system saw the creation of common rules for bank registration. The regulatory regime in the latter half of the period is relatively ‘hands-off’ compared with a considerably more interventionist system early in the period (Wallis Inquiry, 1997, p. 567-597; Davis, 2004, p. 9-15).

The observation period covers the major banking system crisis which occurred in 1990/1991. The state banking system was affected by the 1991 demise of both the State Bank of South Australia (later absorbed into a predecessor of St. George Bank) and State Bank of Victoria (amalgamated into Commonwealth Bank of Australia). Other Australian banking firms also suffered during these years, most notably market leader Westpac following its involvement in some high profile failed commercial real estate projects.¹

The fallout of the system crisis led to a substantial re-shaping of the banking scene. All Commonwealth and state government owned institutions were privatized and in most cases later absorbed into other banks. Australia’s banking market concentration saw the emergence of four leading banking groups (ANZ, CBA, NAB and Westpac).

This paper utilises a database of financial and credit loss information for a sample of Australian banks for the period 1980 to 2005 which was compiled in and discussed by Hess (2008). The data have been retrieved from original bank reports of all Australian banks excluding (1) institutions that are predominantly wholesale and/or merchant banks and (2) non-bank financial institutions. To construct the asset recovery proxy, one needs information about the level of impaired bank assets (gross value) and the corresponding estimate of expected realizable value. The realizable value as a percent of gross impaired assets is the implied recovery rate on distressed bank assets (see the Appendix for more background on the construction of this proxy). The first bank to provide such information was National Australia Bank (NAB) in 1982.

Table 1 provides information about the 18 banks in the sample and the availability of relevant asset recovery data. Figure 1 plots the times series of implied recovery rates for the four major Australian banks. Our investigation utilizes recovery rates from 1989 onwards when numerous banks started reporting this item.

¹ Westpac’s cumulative write-offs from 1990 to 1993 represented about 8% of loans outstanding. See Carew (1997) and Davidson & Salisbury (2005) for an account of Westpac’s crisis.

Table 1. Overview of Banks in Database and the Availability of Recovery Data

Bank identifier	Bank full name	Institution earlier name	Successor	Registered	Recovery data
AU AdelaideBk	Adelaide Bank	Co-operative Building Society of South Australia	AU BendigoBk	1994 to 2008	1992-2005
AU AdvanceBk	Advance Bank	NSW Building Society	AU StGeorge	1985 to 1998	1989-1995
AU ANZ	ANZ Banking Group (AUS)			whole period	1989-2005
AU BendigoBk	Bendigo Bank	Bendigo Permanent Land and Building Society		1995 to present	1995-2005
AU BkMelbourne	Bank of Melbourne	RESI Statewide Building Society	AU Westpac	1989-1998	1990-1996
AU BkWest	Bank West	Rural & Industries Bank of Western Australia	HBOS, AU CoWthBk since 2008	whole period	1991-2004
AU BoQ	Bank of Queensland			whole period	1992-2005
AU ChallengeBk	Challenge Bank	Hotham Permanent Building Society (Vic)/ Perth Building Society	AU Westpac	1987 to 1996	1989-1995
AU Colonial*	Colonial / Colonial State Bank	Colonial Mutual Life Assurance Society, took over AU SBNSW	AU CoWthBk	1995 to 2001	1995-1999
AU CoWthBk	Commonwealth Bank			whole period	1984-2005
AU EldersRural	Elders Rural Bank Limited			2000 to present	1999-2005
AU NAB	National Australia Bank	National Bank of Australasia		whole period	1982-2005
AU PIBA	Primary Industry Bank of Australia		Rabobank Australia	1987 to 2003	1989-1993
AU SBNSW*	State Bank of New South Wales	Rural Bank of New South Wales	AU Colonial	to 1994	1990-1994
AU SBSA	State Bank of South Australia	The State Bank of South Australia	AU Advance Bk	to 1994	1990-1994
AU StGeorge	St.George Bank	St.George Building Society	AU Westpac	1993 to 2008	1992-2005
AU Suncorp	Suncorp	Metway Bank	AU Westpac renamed Suncorp in 2002	1988 to present	1991-2005
AU Trustbk TAS	Trust Bank Tasmania	SBT Bank (The Savings Bank of Tasmania), Hobart Savings Bank	AU CoWthBk	to 1999	1992-1998
AU Westpac	Westpac (AUS)	Bank of New South Wales		whole period	1985-2005

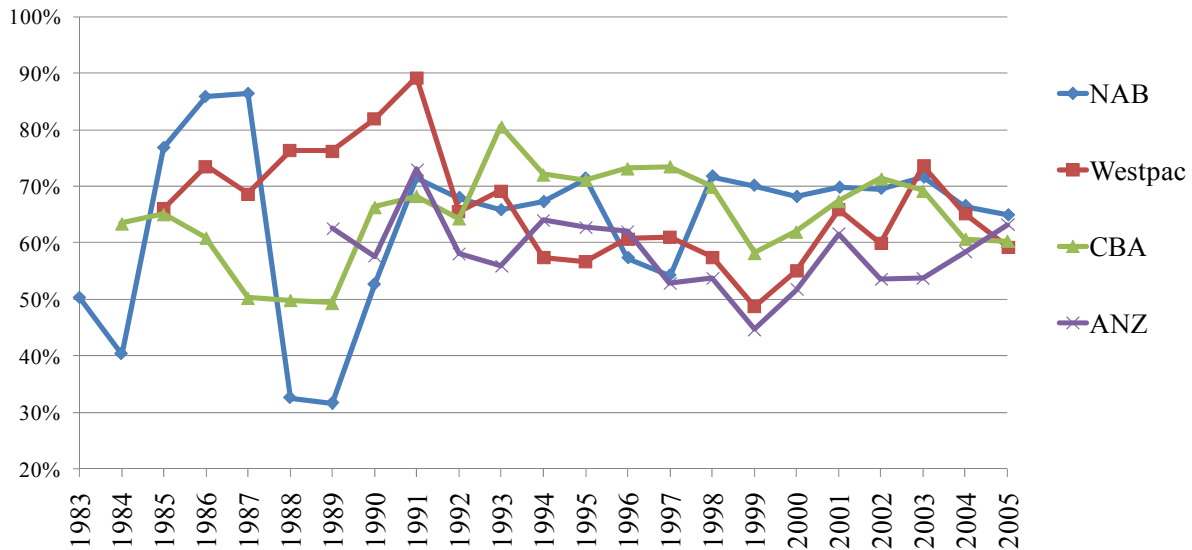
Notes:

*AU SBNSW and successor AU Colonial are treated as one time series in this empirical research.

The following banks, operating earlier in the observation period, were omitted from the sample due to missing data: Commercial Banking Company of Sydney Limited, Commercial Bank of Australia, State Bank of Victoria, Tasmania Bank.

All data are annual.

Figure 1. Implied Recovery Rates (RCV_IA) of Major Australian Banks



Movements in macroeconomic variables are likely to affect asset quality and thus recovery values. Two indicators are used as explanatory variables for the cyclical state of the economy, GDP growth (GDPGRW) and the change in the rate of unemployment (Δ UNEMP); we employ these variables alternatively given the high correlation between them over the sample ($\rho = -0.87$). Asset market developments may also affect asset quality and borrowers' cash flows, consequently impacting on the value of collateral held by banks. We concentrate on three asset market variables, the percentage change in the housing price index (HPGRW), the return on the national share index (RET_SHINDEX) and changes in real interest rates (REALINTGRW).²

Controls are required for bank-specific drivers of recovery rates since we are dealing with a heterogeneous sample of banks that ranges from small regional mortgage lenders to multi-line internationally diversified institutions. We focus on the institution's net interest margin (NIM). In part, NIM can be viewed as a proxy for the institution's risk appetite. If risk appetite were the key determinant of NIM, we would expect a high NIM to be associated with lower recoveries in the event of default as the result of a riskier loan book. However, NIM is negatively correlated ($\rho = -0.30$) with the institution's share of system loans (SH_SYSLNS) implying that smaller (generally retail focused) banks have wider margins than do larger banks (reflecting operational costs of retail banking). In this circumstance, we would expect a high NIM to be associated with a higher recovery rate given retail banks' reliance on traditional home lending with solid collateral in the event of default. Given the negative correlation between NIM and SH_SYSLNS, we expect this latter (positive) relationship between NIM and the recovery rate to predominate.

² Earlier work also considered CPI inflation, a constituent part of nominal interest rates, but the additional term did not yield robust results.

To account for other bank characteristics, including potential behavioural influences on provisioning levels, we include a bank's earnings before taxes and loan loss provisions as a proportion of its average total assets (EBTP_AS) as an explanatory variable. It has been argued that management has an incentive for smoothing reported income by means of discretionary provisions (seminal work by Greenawalt and Sinkey Jr., 1988). Specifically we hypothesise that management in banks with good (poor) current performance relative to future performance will 'save' income for ('borrow' income from) the future by reducing (increasing) current income through loan loss provisions (Kanagaretnam et al., 2003). Provisions enter the construction of the dependent recovery rate proxy (inverse relationship), so this hypothesis calls for a negative coefficient on the earnings proxy.³

Table 2 provides a description of each of our explanatory variables, including their hypothesised effects. Table 3 provides descriptive statistics for the aggregate macroeconomic and bank-specific series.

Table 2: Description of Variables and Expected Impact on Recovery Rates

	Variable name	Acronym	Expected sign
Dependent variable			
Implied recovery rate	1 minus (specific provisions as a proportion of total impaired assets)	RCV_IA	n.a.
Explanatory variables			
<i>Macroeconomic variables</i>			
Economic cycle	Real GDP growth	GDPGRW	+ve
	Unemployment rate (p.p. change)	□UNEMP	-ve
Asset price movements	Housing price index (% change)	HPGRW	+ve
	Share index (% change)	RET_SHINDEX	+ve
	Point change in real interest rates	REALINTGRW	-ve
<i>Bank-specific variables</i>			
Bank characteristics	Net interest margin	NIM	+ve
	Earnings before taxes and provisions (as % of average assets)	EBTP_AS	-ve

³ Further bank specific proxies have been explored. We included SH_SYSLNS as an alternative variable to NIM (given the correlation between them); results for other variables were little changed. We found no significant effects from the inclusion of a bank's cost-income ratio, or a proxy for the risk characteristics of a bank's loan portfolio (the ratio of the bank's Basel I housing loans to total loans). Accordingly, these results are not incorporated here.

Table 4. Descriptive Statistics (1989 to 2005)*

Acronym	Mean	Median	Maximum	Minimum	Std Dev	Obs
GDPGRW	3.3%	3.7%	5.4%	-0.7%	1.4%	17
HPGRW	6.1%	5.0%	18.0%	-4.2%	6.3%	17
REALINTGRW	-0.1%	-0.3%	4.5%	-2.8%	1.7%	17
RET_SHINDEX	6.32%	7.09%	19.28%	-7.92%	7.50%	17
ΔUNEMP	0.01%	-0.50%	2.39%	-1.61%	1.07%	17
RCV_IA	63.8%	64.6%	95.6%	2.7%	15.1%	189
NIM	2.9%	2.7%	6.8%	0.6%	0.8%	189
EBTP_AS	1.6%	1.6%	8.8%	0.3%	0.7%	189

*The bank-specific series (RCV_IA, NIM, EBTP_AS) each include 18 cross-sections.

3. Empirical Model and Results

We conduct a pooled cross-section time-series analysis on our bank sample,⁴ initially treating it as a dynamic panel; subsequently we examine two alternative model formulations. The dynamic panel approach includes a lagged term of the dependent variable as an explanatory variable, reflecting the observation that the levels of estimated recoveries are ‘sticky’ as management adjusts its assessment of recovery only gradually as new information comes to light (the correlation coefficient between current and lagged RCV_IA is $\rho=0.77$). Similar models are used in macro-prudential literature to explore the dynamics of credit losses in banking (e.g. Salas and Saurina, 2002; Pain, 2003). Accordingly, we initially estimate a model of the form:

$$RCV_IA_{i,t} = \beta_0 RCV_IA_{i,t-1} + \sum_{k=1}^N \beta_k x_{i,k,t} + u_{i,t} \quad (1)$$

where $RCV_IA_{i,t}$ is the dependent variable, realizable value as a percentage of gross impaired assets for bank i in year t . On the right hand side of the equation are the lagged dependent variable plus N potential explanatory variables, x , from the list of variables defined in Table 2; $u_{i,t} \sim (0, \sigma^2)$ is the error process.

The presence of the lagged dependent variable in the dynamic model raises particular issues for panel estimation procedures. This is because any time-invariant bank-specific effect, which shows up in the error term, will be correlated with the lagged dependent variable. As a result OLS and GLS procedures will produce biased and inconsistent coefficient estimates.

⁴ Earlier research on this data sample, examining drivers of credit losses, showed that Australian banks have responded similarly to common variables (Hess et al., 2009).

To overcome this correlation between the errors and the lagged dependent variable, we apply the Arellano and Bond (1991) generalised method of moments estimator which optimises across the available set of instruments to produce consistent parameter estimates for the dynamic model.

We begin with a model incorporating aggregate macro and bank-specific variables discussed in section 2. To avoid problems of multicollinearity, we include either the GDP growth rate (GDPGRW) or the change in the unemployment rate (Δ UNEMP) separately as the macroeconomic indicator. The resulting estimates are presented in the first two columns of Table 4. As well as the macroeconomic variables discussed above, we include each of the real interest variable (REALINTGRW), the two asset market proxies for the share and housing markets (RET_SHINDEX and HPGRW respectively),⁵ the bank's net interest margin (NIM), and the bank's earnings proxy (EBTP_AS).

Table 1. Estimation Results

Dependent Variable	RCV_IA	RCV_IA	RCV_IA	RCV_IA	D_RCV_IA	D_RCV_IA
Estimation Method	GMM	GMM	OLS	OLS	OLS	OLS
Fixed Effects (Y/N)	N	N	Y	Y	N	N
Explanatory Variables						
<i>RCV_IA (-1)</i>	-0.059*	-0.028				
<i>GDPGRW</i>	-2.002***		-1.106*		-12.676***	
<i>ΔUNEMP</i>		1.884***		1.553*		19.323***
<i>REALINTGRW</i>	-1.506***	-1.538***	-1.204*	-1.153*	6.773	7.887
<i>RET_SHINDEX</i>	0.159***	0.135***	0.022	0.045	-1.533	-1.309
<i>HPGRW</i>	-0.003	-0.043	0.086	0.059	0.553	0.178
<i>NIM</i>	14.576***	11.495***	4.935***	4.696***	9.829	7.675
<i>EBTP_AS</i>	-5.813***	-3.363***	-3.161**	-3.034**	6.770	7.093
Observations	168	168	198	198	181	181
R²	n.a.	n.a.	0.582	0.528	0.055	0.062
1st order auto-corr., p-value	0.602	0.224	n.a.	n.a.	n.a.	n.a.
Durbin-Watson	n.a.	n.a.	0.998	1.008	2.016	2.026

Notes: ***, ** and * denote significance at the 1, 5 and 10 per cent levels, respectively. Estimation is for observation period 1989 to 2005 for 18 banks (see Table 1). Variables are explained in Table 2 (other than D_RCV_IA, defined in the Appendix, Part 2); constant not reported. GMM equations estimated as a dynamic panel with first-difference estimation as cross-section effects method, GMM weighting according to White period system covariances (Arellano-Bond 2-step/n-step). All t-statistics use White period standard errors (d.f. corrected). Indicated OLS equations are estimated with cross-section fixed effects (Fixed Effects = Y).

⁵ We have estimated the equations variously with RET_SHINDEX and HPGRW both included, and included separately; results are very similar and so we only report the results where both variables are included.

Our GMM results pertaining to the determinants of expected bank loan recoveries are distinctly different from prior results relating to corporate bond recoveries. Studies of the latter generally find depressed recoveries in years of weak economic growth (Fridson et al., 2000; Frye, 2000, p.13; Carey and Gordy, 2004). By contrast, our results indicate that bank loan recoveries are higher (lower) in years of economic contraction (growth). The coefficients on both GDPGRW and Δ UNEMP are significant at the 1% level.

Behavioural factors within banks possibly lie behind these results. For one, efforts to recover defaulted debt in a good year could be hampered by the organisation's focus on growing the lending portfolio; i.e. debt recovery may not be the focus of management in a boom phase. Conversely, tough economic times may see the build-up of specialist debt work-out capacity and collateral requirements might be more strictly enforced.

Another explanation for this result (consistent with Hess et al., 2009) is that bank management may use its discretion to set credit loss provisions in line with their own interests (noting that our recovery proxy has been constructed using the banks' own specific provisions). A number of studies have observed earnings smoothing patterns when banks put off provisions in bad years while using their discretion to provision for high levels of bad debt in good years (see literature reviewed in Lobo and Yang, 2001, p. 225-227). If management understates provisions in a downturn, their implicit recovery estimate will be inflated. This interpretation is supported by negative (and significant) coefficients on the bank specific earnings proxy (EBTP_AS), consistent with earnings management practices. This second behavioural interpretation would imply that bank management uses its discretion mainly with regard to specific provisions but not the level of impaired assets which also enters the calculation of the recovery proxy but does not have a direct impact on bank earnings.

While the property price proxy (HPGRW) is not significant, strong share market performance (RET_SHINDX) does appear to positively influence bank management's expectation of asset recoveries. The share price is a readily observable indicator that may be a leading indicator of economic cycles, although the latter property is far from conclusive (e.g. Pearce, 1983). Nevertheless, the equity market may have a 'mood effect' with bull and bear markets affecting the subjective assessment of recovery values by banks. Such mood effects have been documented in psychology (Wright and Bower, 1992) and have been blamed for contributing to the recent economic crisis as risk managers inappropriately calibrated their risk models.

The GMM results indicate that changes in real interest rates have a significant negative impact on recoveries. Banks might find it genuinely difficult to collect bad debts in an environment of rising interest rates. An alternative interpretation is that a time of rising interest rates often coincides with an economic growth phase with tight monetary policies (confirmed by the correlation coefficient between REALINTGRW and GDPGRW of

$\rho=0.32$.) Our interest rate result proxy might thus be another manifestation of the effect for GDPGRW.

Bank specific control parameters are significant at the 1% level. Wide net interest margin banks are typically small, retail focussed institutions. Such institutions exhibit, on average, higher recovery rates, consistent with these banks concentrating on traditional home lending, typically with solid collateral values. The negative coefficient for the earnings proxy EBTP_AS is consistent with an earnings smoothing motive. It is also consistent with the effects of ‘signalling through loan loss provisions’ (Beaver et al., 1989). Wahlen (1994) offers evidence that bank managers appear to increase the discretionary component of current loan loss provisions when future cash flow prospects are expected to improve. It is argued that the bank thus signals strength to the market because it is able to provision more conservatively than its peers.

One surprising feature of the dynamic GMM results is that the coefficient on the lagged dependent variable is close to zero and is not significant at the 5% level in either equation. To test the robustness of our empirical results to alternative dynamic specifications, the model of equation (1) has been estimated with two alternative formulations.

First, we estimate the equations using a static specification (i.e. excluding the lagged dependent variable) using OLS (an appropriate estimator in this case). For this static specification we include bank fixed effects (a Wald test of these terms rejects the null hypothesis that they are redundant at less than 0.1%). These fixed effects control for underlying unchanging bank-specific characteristics within the sample. The results are presented in columns 3 and 4 of Table 4 with t-statistics calculated using robust White diagonal standard errors (White, 1980) given the equations’ low Durbin-Watson statistics (of approximately 1). The results are similar to those of the GMM estimates. Coefficients on the main macro variables (GDPGRW, DUNEMP, REALINTGRW) remain significant (albeit now at the 10% level), although the other asset price variables are not significant. The bank-specific controls, NIM and EBTP_AS, remain consistently significant.

The insignificance of the lagged recovery rate in the GMM specification runs counter to our hypothesis that estimated recovery rates tend to be sticky across years, and this result could be due to weak instruments available for the GMM estimation. The significant autocorrelation of residuals in the static OLS specification indicates that some degree of stickiness in recoveries is actually observed in practice. We test the robustness of our results with an alternative dynamic specification, adopting a transformation of the dependent variable derived by manipulating the definition of RCV_IA_{it} and of its lag. The resulting dependent variable, derived explicitly in Part 2 of the Appendix, results in our estimating the determinants of the change in recoveries scaled by the bank’s gross impaired assets. This variable is denoted D_RCV_IA_{it}, and is defined as:

$$D_RCV_IA_{it} \equiv RCV_IA_{it} - (G_{it-1}/G_{it}) RCV_IA_{it-1}$$

where G_{it} is bank i 's gross impaired assets at time t . If the level of gross impaired assets is identical across periods, $D_RCV_IA_{it}$ is simply the change in our levels recovery variable.

Columns 5 and 6 of Table 4 present the results with $D_RCV_IA_{it}$ as the dependent variable. In this case, since we are estimating a change variable, we do not include bank fixed effects. Consistent with the prior results for the macroeconomic variables, we again find strong counter-cyclical effects on recoveries (the coefficients for $GDPGRW$ and $DUNEMP$ are both significant at the 1% level). Other variables are not significant once the dependent variable is essentially differenced, i.e. the differencing effectively captures the influence of the bank specific effects. The Durbin-Watson statistic of approximately 2.02 in each equation indicates that this specification of the dependent variable does capture the essential dynamics of the recoveries process. Even with this differencing, our core conclusion that banks' expected recoveries are counter-cyclical, remains intact.

6. Conclusions

Our findings indicate that banks' expected recovery rates improve in bad economic times, contrary to existing literature analysing defaulted bond (rather than bank loan) recoveries that has predominantly found the reverse relationship. The recovery proxy used in this study is based on a bank's own estimate of impaired assets and corresponding credit loss provisions. These estimates may be formulated in line with bank management's own interests, in particular to smooth earnings and/or to signal strength through generous provisioning.

Real interest rate increases may affect the level of recoveries (negatively) but do not affect the change in recoveries, while other asset price variables do not have a consistent effect on recovery rates. Banks with high net interest margins (predominantly retail banks) tend to have high expected recovery rates, although changes in recovery rates are not affected by this margin. Banks with high earnings ratios report lower expected recovery rates (potentially consistent with an earnings smoothing motive) but their changes in recovery rates are unaffected by this influence.

Overall, our findings indicate that projected recovery rates for bank loans are affected strongly by the economic cycle, in a manner that is inconsistent with the cycle's effect on corporate bond recovery rates. Our recovery proxy reflects the subjective judgement of bank management concerning expected recoveries, and such expected outcomes, by their nature, reflect forward-looking judgements. 'Fundamentals' also play a part. For instance, (predominantly retail) banks with high net interest margins have higher expected recovery rates, consistent with high quality collateral backing for their loans (e.g. for housing mortgages). The nature of such loans may help to explain the difference between our results (for bank loans) and those of other studies with respect to corporate bonds. This contrast in

results reflects either differing fundamental behaviour in recoveries for alternative loan types or the differing latitude of bank management to apply judgement to their own loans relative to the market's judgement on corporate bonds.

Our sample predominantly covers the 'Basle I' period; i.e. prior to the introduction of the Basle II standards and the introduction of IFRS (International Financial Reporting Standards), both of which have changed provisioning standards. An extension of the current study could analyse whether banks' judgements regarding estimated recoveries has changed with the introduction of these new standards. In addition, application of our approach to other markets with a wide array of banks (e.g. the USA) could indicate whether the relationships that we have determined are general across (all or certain types of) banks or are specific to the Australian banking market.

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Appendix

Part 1: Construction of Recovery Rate Proxy

Under Australian accounting standards in force since the early 1990s, a bank raises a specific provision as soon as a loan has been identified as doubtful and when the estimated repayment realisable from the borrower is likely to fall short of the amount of principal and interest outstanding. Such loans are then reported as part of the bank's impaired assets and typically constitute the major component included under this accounting item. There are other, usually smaller, asset categories included under impaired assets. For example, Australian Prudential Regulation Authority (APRA) guidelines for classifying impaired assets also require banks to include restructured assets where the original contractual terms have been modified to provide for concessions of interest or principal for reasons related to the financial difficulties of the customer. While the precise definitions of what constitutes an impaired asset might have changed through time, they can essentially be considered as distressed or defaulted assets on which the bank provides a best estimate of a loss given default (LGD) in the form of a specific provision.

We can use the approach above to construct the expected recovery rate proxy (RCV_{IA}) as follows:

$$RCV_{IA} = 1 - \frac{\textit{Specific provisions}}{\textit{Gross impaired assets}} \quad (A1)$$

RCV_{IA} thus provides us with a time series of net realizable value expressed as a % of gross defaulted bank assets for a diversified portfolio of bank assets subject to credit risk.

Part 2: Alternative Dependent Variable

In order to estimate an equation with no lagged dependent variable, while recognising the ‘stickiness’ in recoveries over time, we manipulate the definition of RCV_IA, from (A1) above, so as to include the lagged impact of recoveries within the dependent variable. The derivation is as follows (where the i subscript is dropped for convenience). Define: $R_t \equiv$ RCV_IA in year t ; $S_t \equiv$ specific provisions in t ; and $G_t \equiv$ gross impaired assets in t . Then from equation (A1):

$$R_t = 1 - S_t/G_t \quad (A2)$$

$$R_{t-1} = 1 - S_{t-1}/G_{t-1} \quad (A3)$$

$$\begin{aligned} \text{Hence: } \Delta R_t &= S_{t-1}/G_{t-1} - S_t/G_t \\ &= S_{t-1}/G_{t-1} - [(S_{t-1} + \Delta S_t)/(G_{t-1} + \Delta G_t)] \\ &= [S_{t-1}(G_{t-1} + \Delta G_t) - S_t G_{t-1} - \Delta S_t G_{t-1}] / [G_{t-1}(G_{t-1} + \Delta G_t)] \\ &= [S_{t-1} \Delta G_t - \Delta S_t G_{t-1}] / [G_{t-1}(G_{t-1} + \Delta G_t)] \\ &= [S_{t-1}(\Delta G_t/G_{t-1}) - \Delta S_t] / G_t \\ &= [(S_{t-1} \Delta G_t) / (G_{t-1} G_t)] - [\Delta S_t / G_t] \\ &= [(1-R_{t-1}) \Delta G_t / G_t] - [\Delta S_t / G_t] \end{aligned}$$

$$\begin{aligned} \text{Hence: } R_t &= R_{t-1} + [(1-R_{t-1}) \Delta G_t / G_t] - [\Delta S_t / G_t] \\ &= (1 - \Delta G_t/G_t) R_{t-1} + [(\Delta G_t - \Delta S_t) / G_t] \end{aligned}$$

$$\text{Thus: } R_t - (G_{t-1}/G_t) R_{t-1} = [(\Delta G_t - \Delta S_t) / G_t] \quad (A4)$$

We adopt $[R_t - (G_{t-1}/G_t) R_{t-1}]$ as a dependent variable; the explanatory variables then explain the change in expected recoveries, i.e. $(\Delta G_t - \Delta S_t)$, as a ratio of gross impaired assets. The dependent variable is denoted D_RCV_IA in the paper.